Real-Time Simulation for Power and Energy Systems with AI Applications

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Outline

- Introduction
- Artificial Intelligence
- RTPIS Lab
- Selected Case Studies
- Summary

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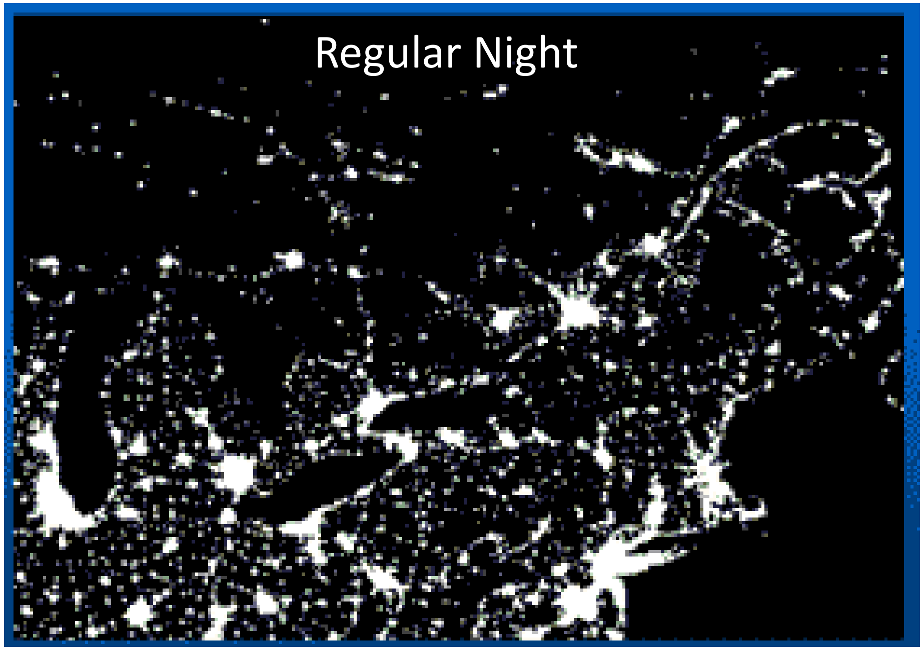
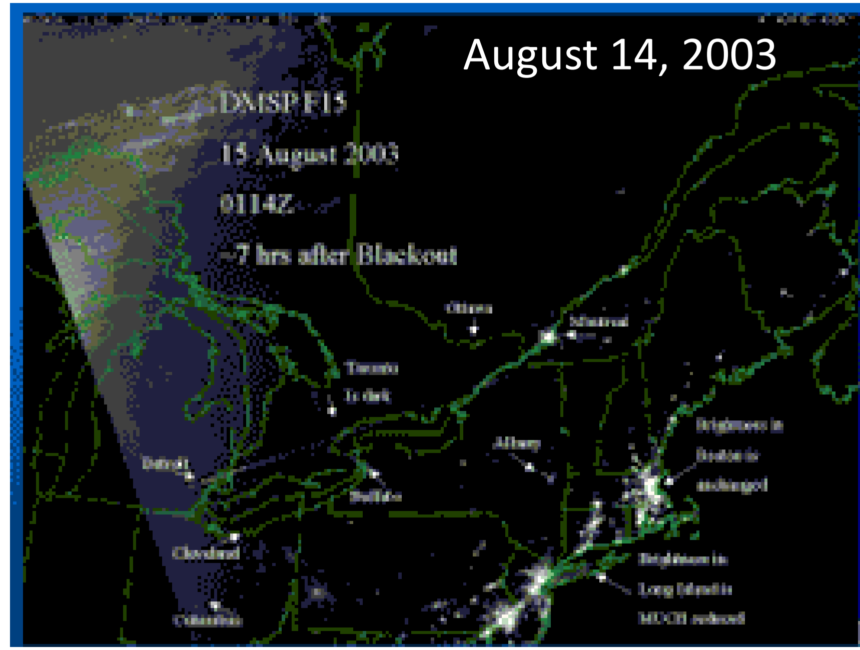
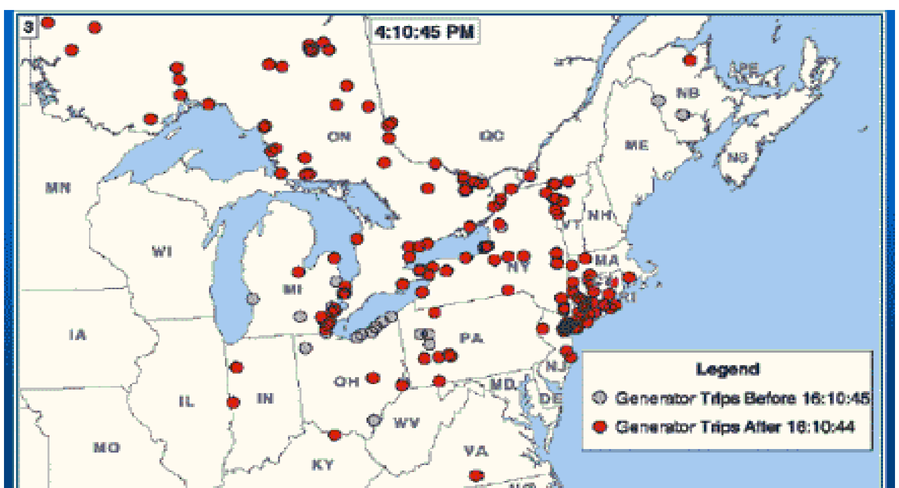
August 14, 2003 Blackout

IEEE Spectrum February 2005







- > 60 GW of load loss;
- > 50 million people affected;
- Import of ~2GW caused reactive power to be consumed;
- Eastlake 5 unit tripped;
- Stuart-Atlanta 345 kV line tripped;
- MISO was in the dark;
- A possible load loss (up to 2.5 GW)
- Inadequate situational awareness.

Complexity of the Grid

- The electricity infrastructure is a complex adaptive system consisting of a range of energy sources including fossil fuel, nuclear, renewable resources, and energy storage with many operational levels and layers including power plants, transmission and distribution networks and control centers.

- The interactions of various power system elements, including physical components and human beings, also increase the complexity of the power grid.

- On the other hand, the diversity of the time scale involved in the operation of different power system elements, further adds to this complexity.

- The time scales for various control and operation tasks can be as short several microseconds and as long as several years, which makes it even more difficult to model, analyze, simulate, control and operate a power grid, such as the North American power grid.

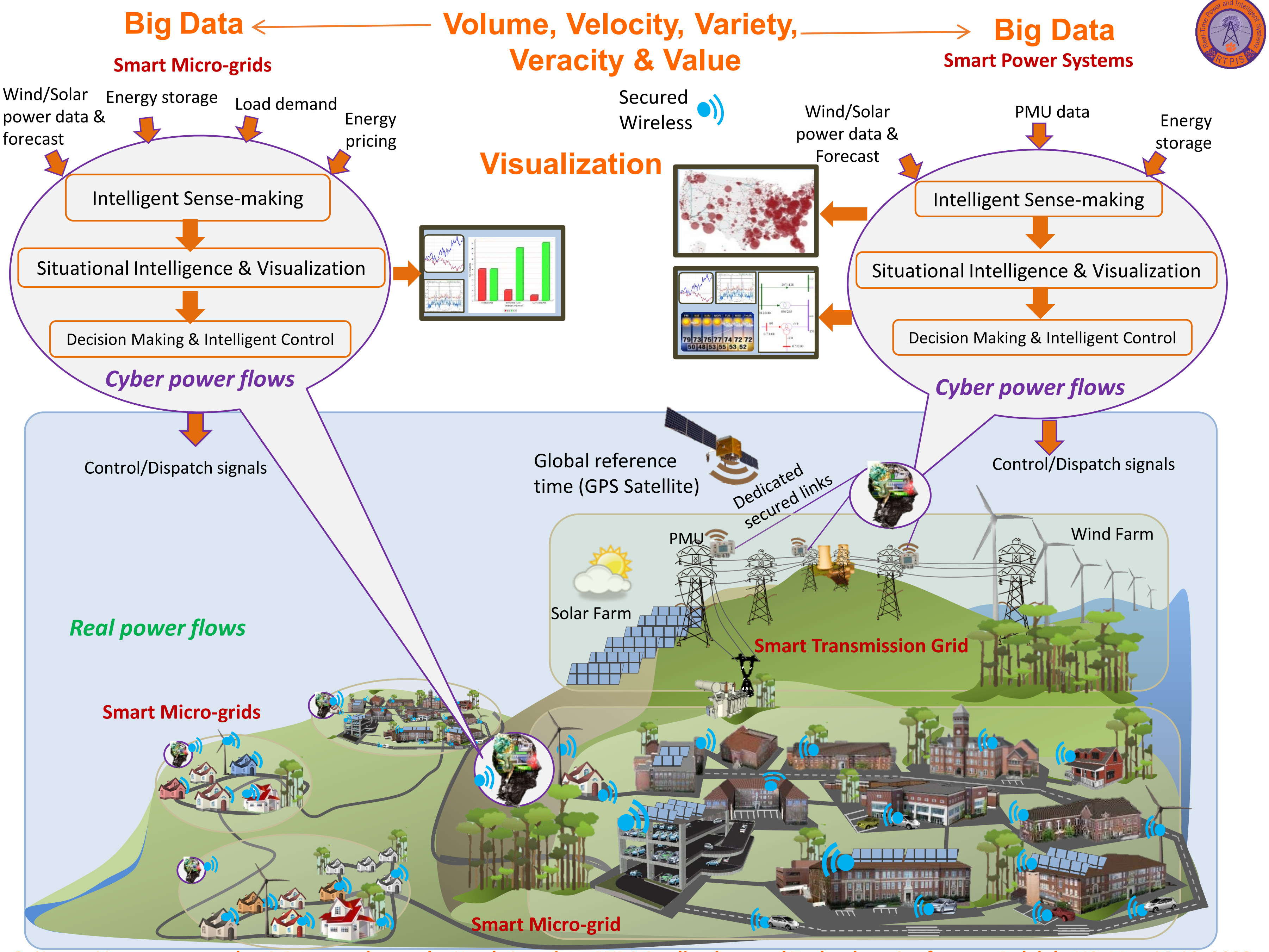
Complexity of the Grid

- Today, operation and control are mostly designed based on *linearized models* of the power system obtained around some nominal operating points.
  - The solutions do not guarantee robustness and good & uniform performance over a wide range of operating conditions.
  - On the other hand, robust and optimal controllers can be designed based on H^{∞} and other classical techniques but these require precise knowledge and accurate high order models.
  - The practical implementation of such control in the real power system is difficult and cumbersome.
- Classical optimization techniques are mostly able to find *local optimum solutions* for power system optimization problems. On the other hand, intelligent optimization techniques can find *near-optimal global solutions*.
- To ensure improved efficiency, reliability, security and sustainability of power & energy systems, advanced computational techniques are needed to *embed intelligence in the grid – the smart grid.*

Smart Grid

A smart grid must have certain basic functions for modernization of the grid (as indicated in the Energy Independence and Security Act of 2007), including:

- Have a self-healing capability.
- Be fault-tolerant by resisting attacks.
- Allow for dynamic integration of all forms of energy generation and storage options including plug-in vehicles.
- Allow for dynamic optimization of grid operation and resources with full cyber-security.
- Allow for incorporation of demand-response, demand-side resources and energy-efficient resources.
- Allow electricity clients to actively participate in the grid operations by providing timely information and control options.
- Improve reliability, power quality, security and efficiency of the electricity infrastructure.

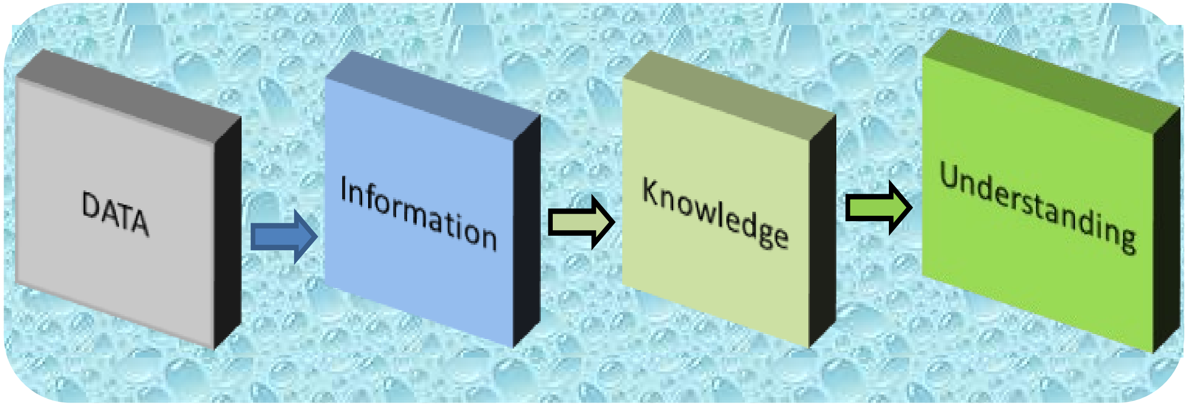

Big Data
Volume, Velocity, Variety,
Veracity & Value
Big Data
Smart Micro-grids
Smart Power Systems
Wind/Solar power data & forecast
Energy storage
Load demand
Energy pricing
Intelligent Sense-making
Situational Intelligence & Visualization
Decision Making & Intelligent Control
Cyber power flows
Secured Wireless
Visualization
Wind/Solar power data & Forecast
PMU data
Energy storage
Intelligent Sense-making
Situational Intelligence & Visualization
Decision Making & Intelligent Control
Cyber power flows
Control/Dispatch signals
Global reference time (GPS Satellite)
Dedicated secured links
Control/Dispatch signals
PMU
Wind Farm
Solar Farm
Smart Transmission Grid
Real power flows
Smart Micro-grids
Smart Micro-grid

Situational Awareness (SA)

- More information (a lot of data) does not necessarily matter in critical operations; rather, what is important is to prioritize the understanding of what matters at the respective instances.

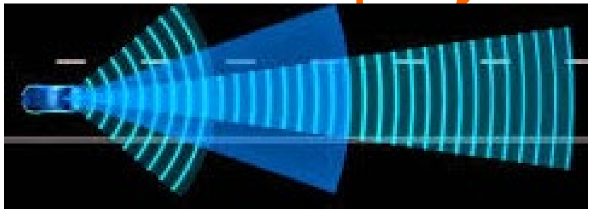
- Sense-making is critical and is a process by which individuals attach a meaning to an experience.

- It is also critical that an understanding be gained from a shared view because the electric power grid is interconnected, and its dynamics are spatially and temporally connected.



Situational Intelligence

- Situational intelligence (SI) is looking ahead how the situations will unfold over time – *immersion into future*
- In other words, situation awareness (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 at 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 $t+\Delta t$.



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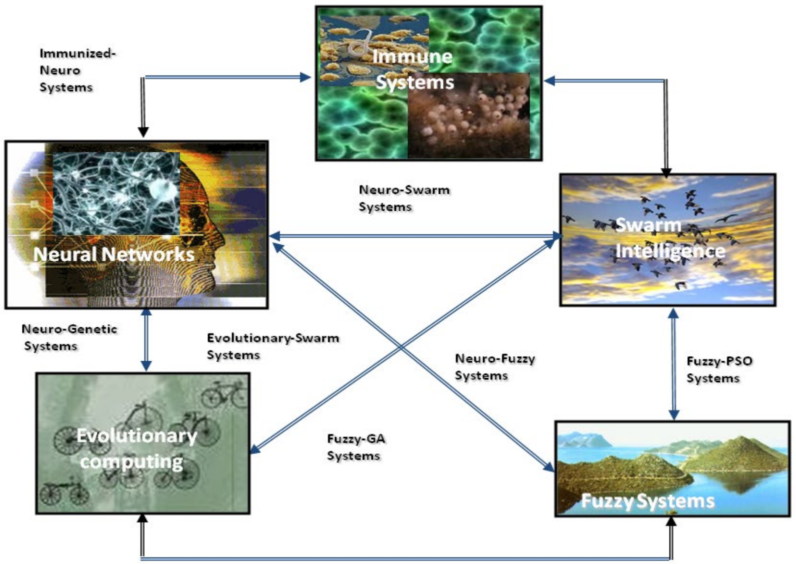
Computational Intelligence

Computational intelligence (CI) can be defined as *computational models and tools of intelligence*

- *capable of taking large raw numerical sensory data directly,*
- *processing them by exploiting the representational parallelism and pipelining the problem,*
- *generating reliable just-in-time responses, &*
- *with high fault tolerance.*

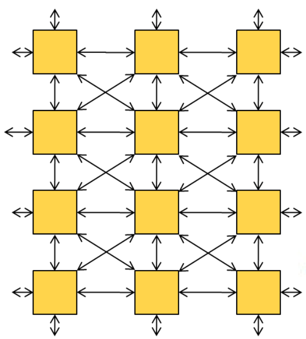
- Artificial immune systems
- Evolutionary computation
- Fuzzy systems
- Neural networks
- Swarm intelligence
- Hybrid systems

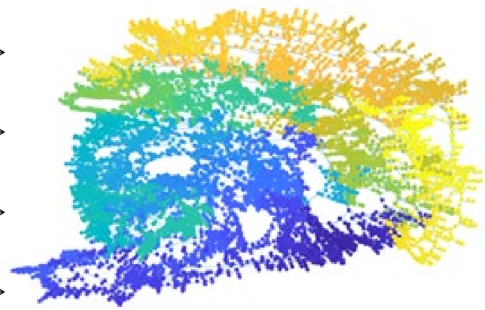


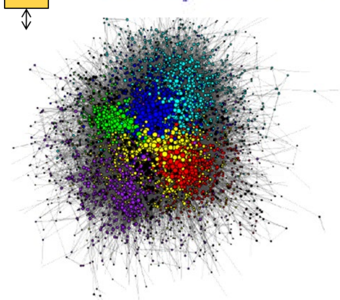
Venayagamoorthy GK, "A Successful Interdisciplinary Course on Computational Intelligence", *IEEE Computational Intelligence Magazine – A special issue on Education*, Vol. 4, No. 1, February 2009, pp. 14-23.

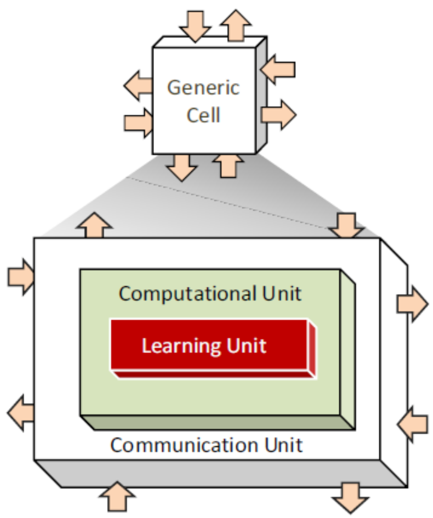
Cellular Computational Networks

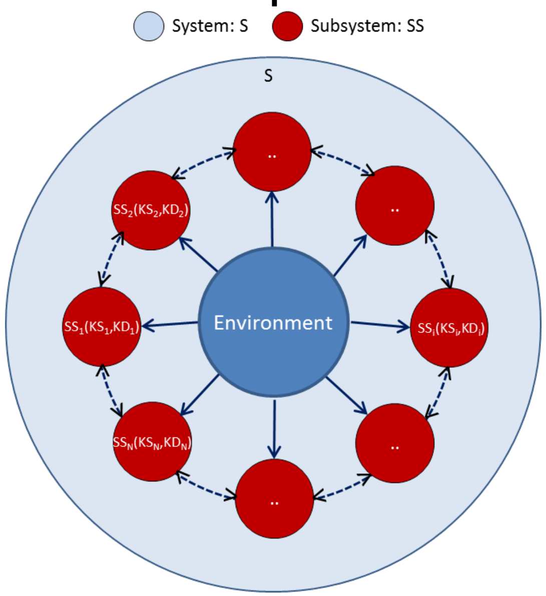
- Cellular computational networks (CCNs) generally consists computational units connected to each other in an ordered distributed manner.
- CCNs are suited to model complex systems with temporal and spatial dynamics.



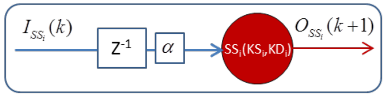








(a)

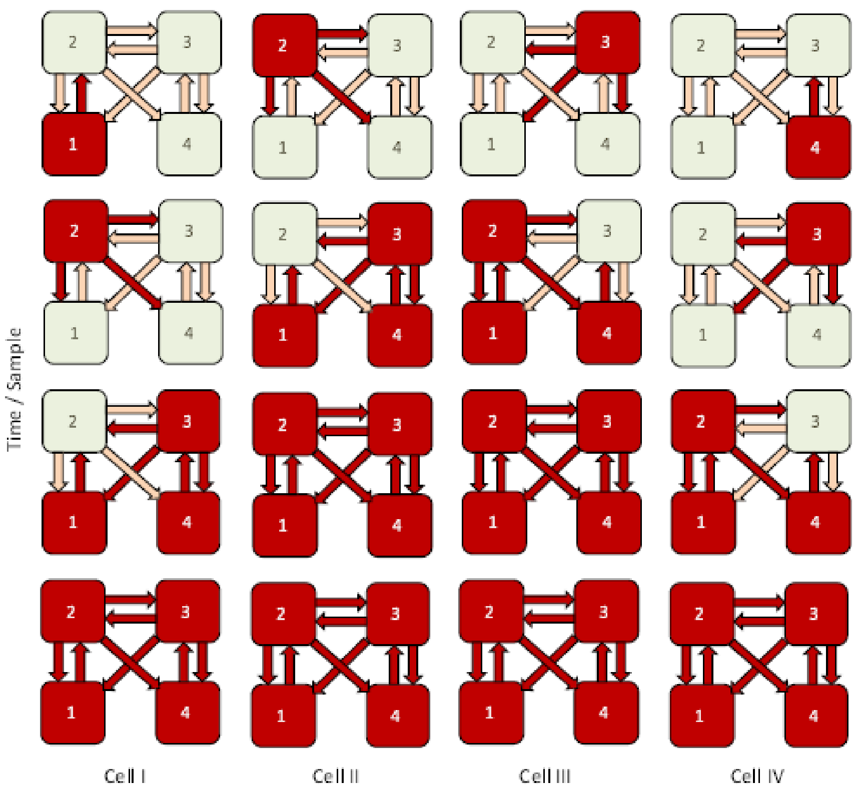


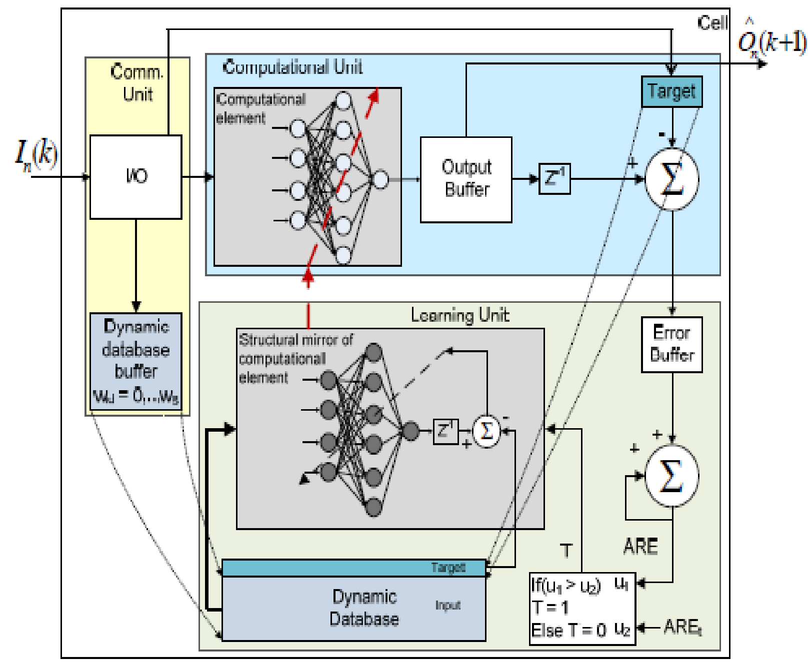
(b)

$$O_{ss_i}(k) = f(\alpha_i O_{SS_i}(k-1), \alpha_n^1 O_{SS_n^1}(k-1), \ldots, \alpha_n^N O_{SS_n^N}(k-1), u(k))$$

Luitel B, Venayagamoorthy GK, "Cellular Computational Networks – a Scalable Architecture for Learning the Dynamics of Large Networked Systems", *Neural Networks*, Vol. 50, February 2014, pp. 120-123.

Asynchronous Learning - CCNs





Luitel B, Venayagamoorthy GK, "Decentralized Asynchronous Learning in Cellular Neural Networks", *IEEE Transactions on Neural Networks*, November 2012, vol. 23. no. 11, pp. 1755-1766,

Adaptive Critics

- The Adaptive critic designs have the potential of replicating critical aspects of brain-like intelligence:

  - ability to cope with a large number of variables in parallel, in real time, in a noisy nonlinear non-stationary environment

- The origins of ACDs are ideas synthesized from combined concepts of approximate dynamic programming, reinforcement learning, and methods for obtaining real-time derivatives (such as backpropagation using neural networks).

- ACDs show a family of promising methods to solve dynamic optimization and optimal control problems.

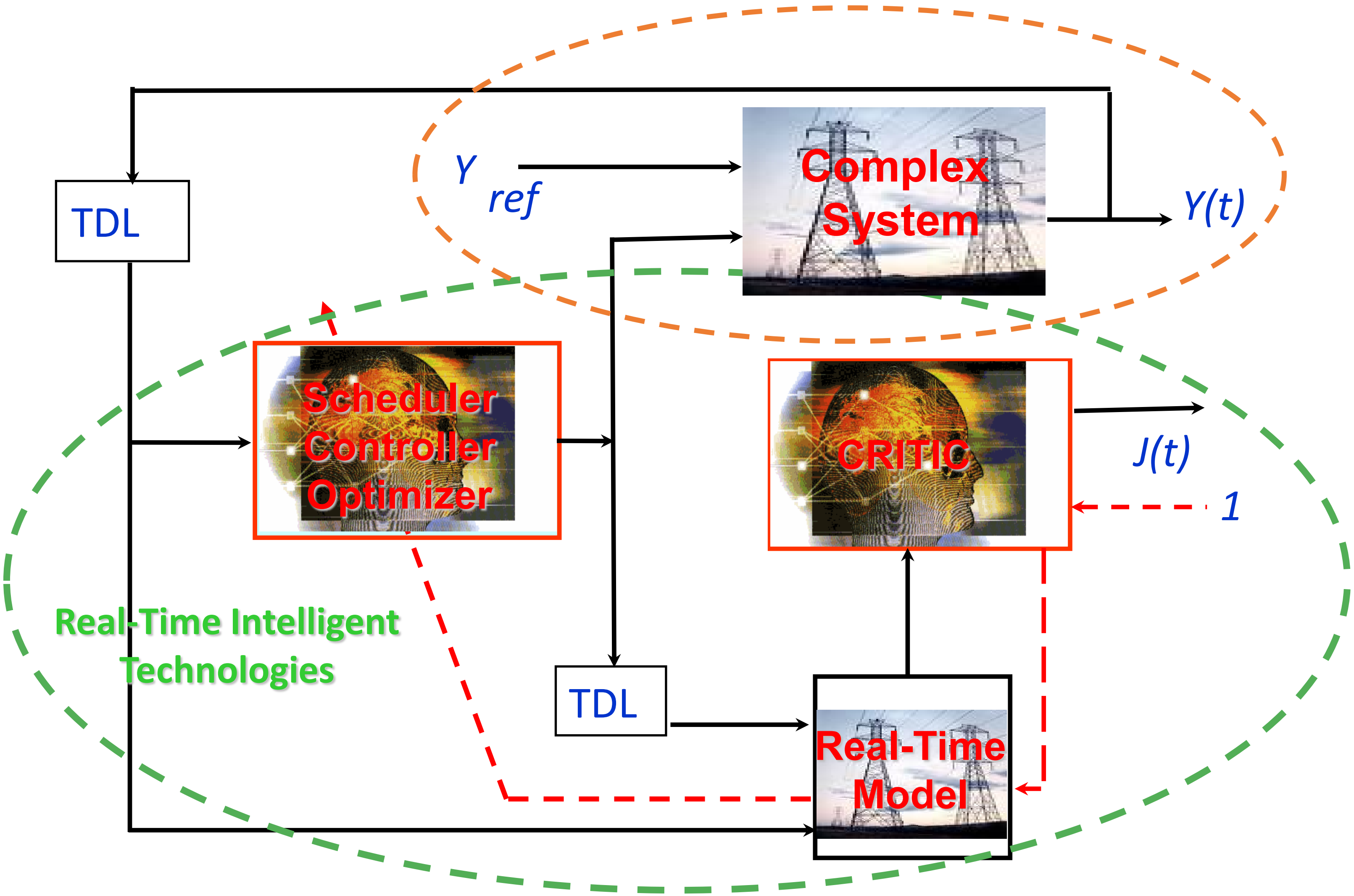
Venayagamoorthy GK, Harley RG, Wunsch DC, "Applications of Approximate Dynamic Programming in Power Systems Control", in *Handbook of Learning and Approximate Dynamic Programming*, Si J, Barto A, Powell W, and Wunsch DC (Eds.), Wiley, July 2004, ISBN 0-471-66054-X, pp. 479-515

Adaptive Critic Designs for Dynamic Optimization of Complex Systems

Venayagamoorthy GK, Harley RG, Wunsch DC, "Comparison of a Heuristic Dynamic Programming and a Dual Heuristic Programming Based Adaptive Critics Neurocontroller for a Turbogenerator", IEEE-INNS International Joint Neural Networks Conference, Como, Italy, July 24-27, 2000, Vol. 3, pp. 233-238

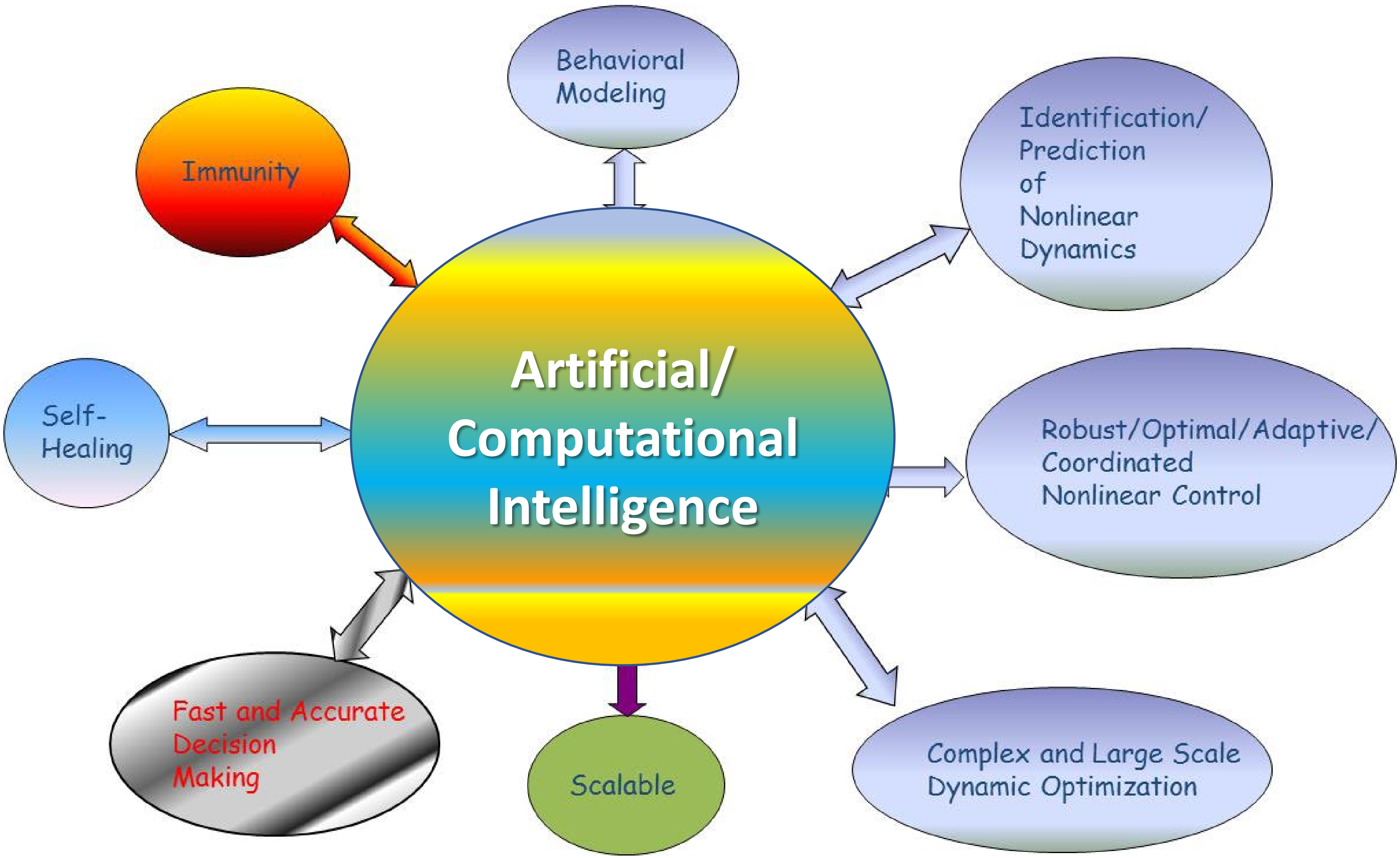
Kulkarni R, Venayagamoorthy GK, "Adaptive Critics for Dynamic Optimization", Neural Networks, Vol. 23, No. 5, June 2010, pp. 587-591

Dynamic Scheduling, Control and Optimization

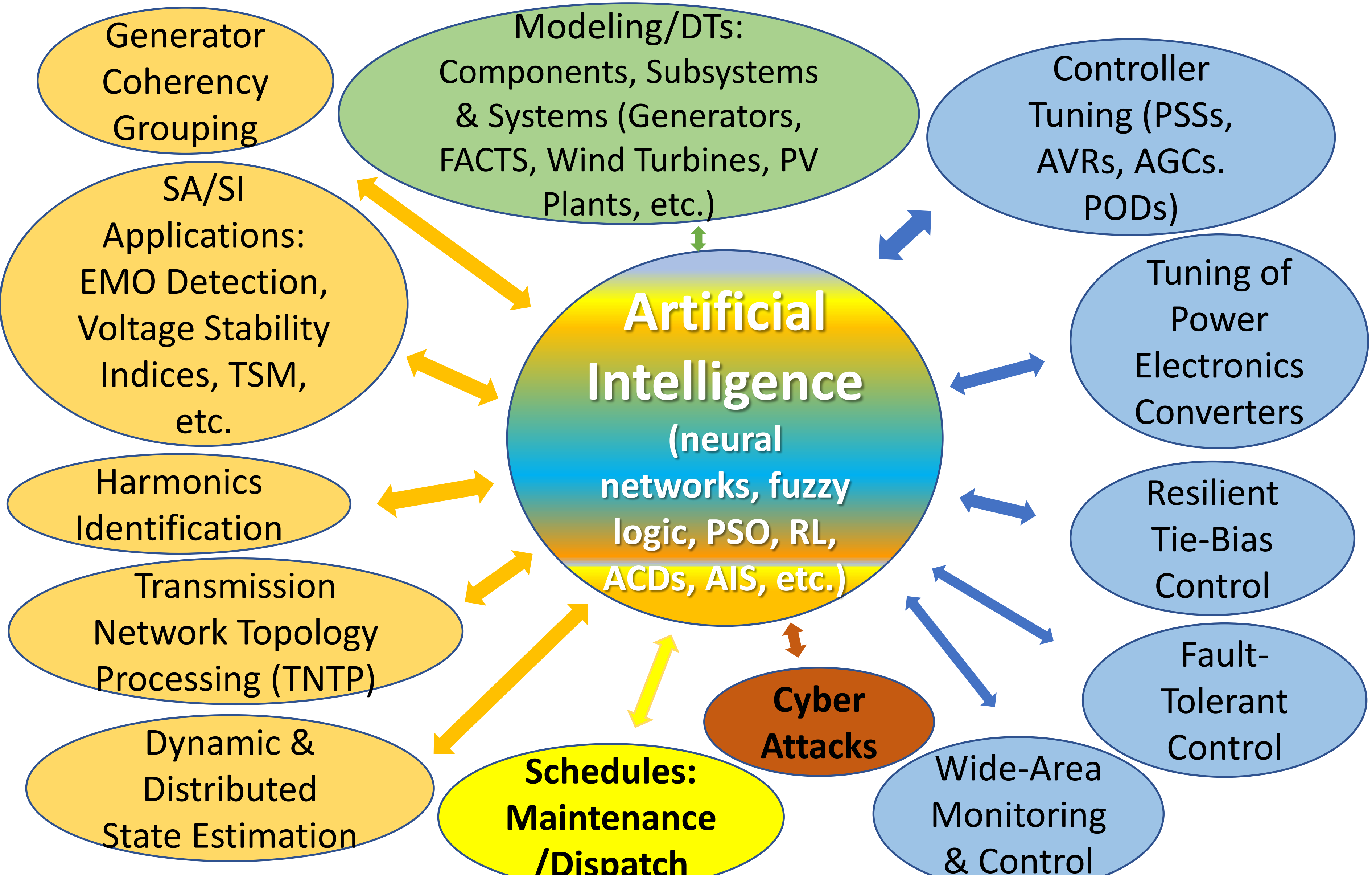


Kulkarni R, **Venayagamoorthy GK**, "Adaptive Critics for Dynamic Optimization", *Neural Networks*, Vol. 23, No. 5, June 2010, pp. 587-591

Potentials and Promises of AI



Applications of AI in PESs



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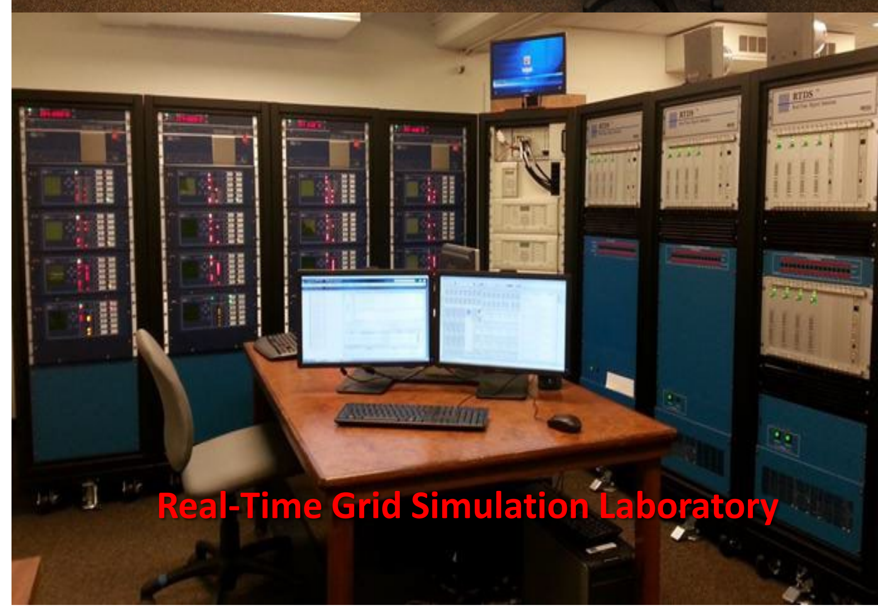
Real-Time Power and Intelligent Systems Laboratory

Emphasis: Research, Education and Innovation-Ecosystem Laboratory for Smart Grid Technologies

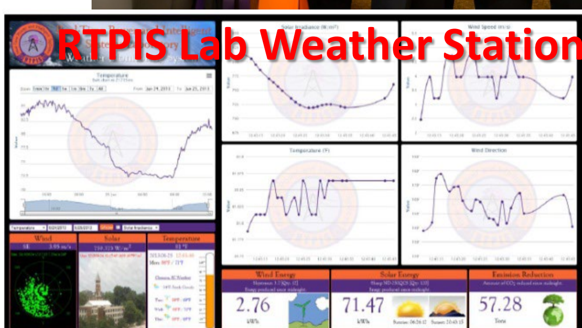
Ribbon Cutting Ceremony – Nov. 7, 2013

Situational Intelligence Laboratory

Real-Time Grid Simulation Laboratory



RTPIS Lab Weather Station and Visualization



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Real-Time Power and Intelligent Systems Laboratory

SEL-2407:
Satellite-Synchronized Clock

SEL-3620:
Ethernet Security Gateway

SEL-3378: Station PDC

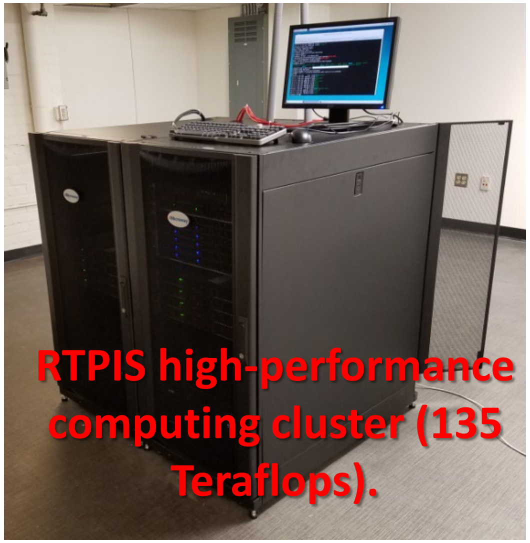
SEL- 411L: Advanced Line Differential Protection, Automation, and Control System

SEL- 421: Protection, Automation, and Control System

SEL- 451: Protection, Automation, and Bay Control System

SEL- 487: Transformer Protection Relay

More information: http:// www.selinc.com



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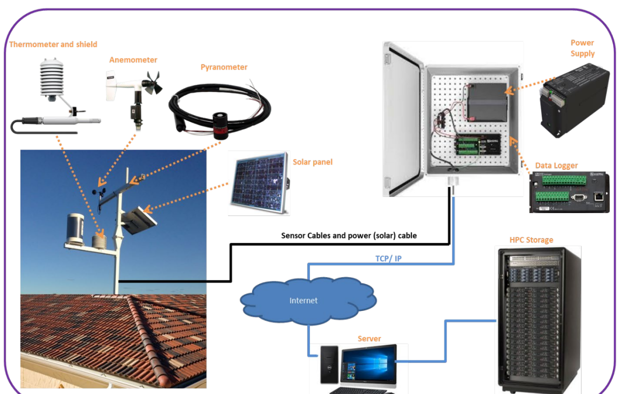
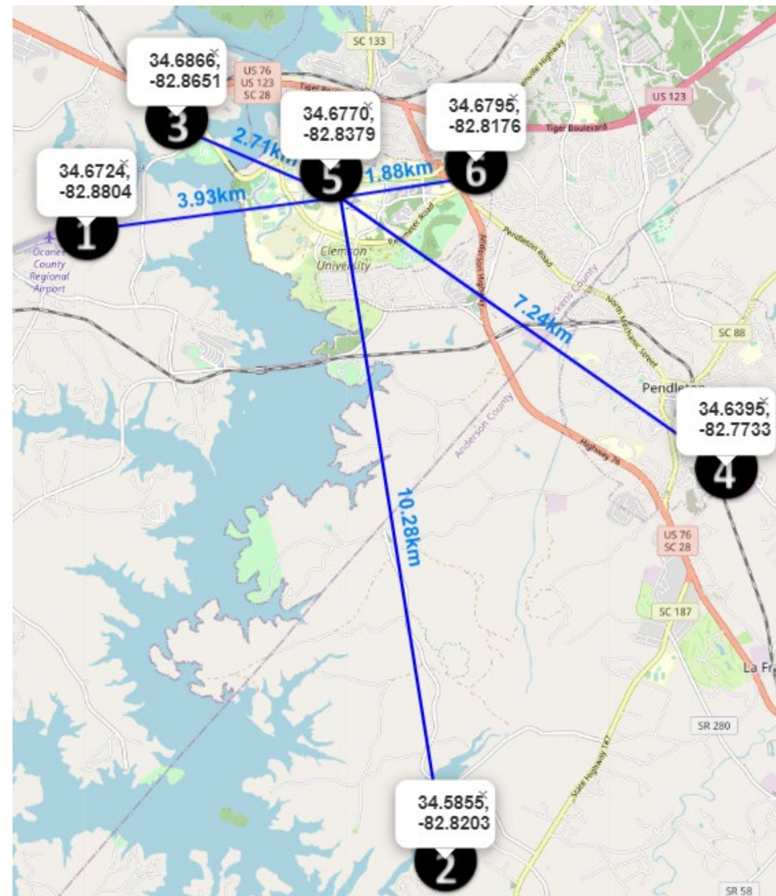
Real-Time Power and Intelligent Systems Laboratory

Clemson University 1 MW PV Plant and RTPIS Lab's Weather Stations





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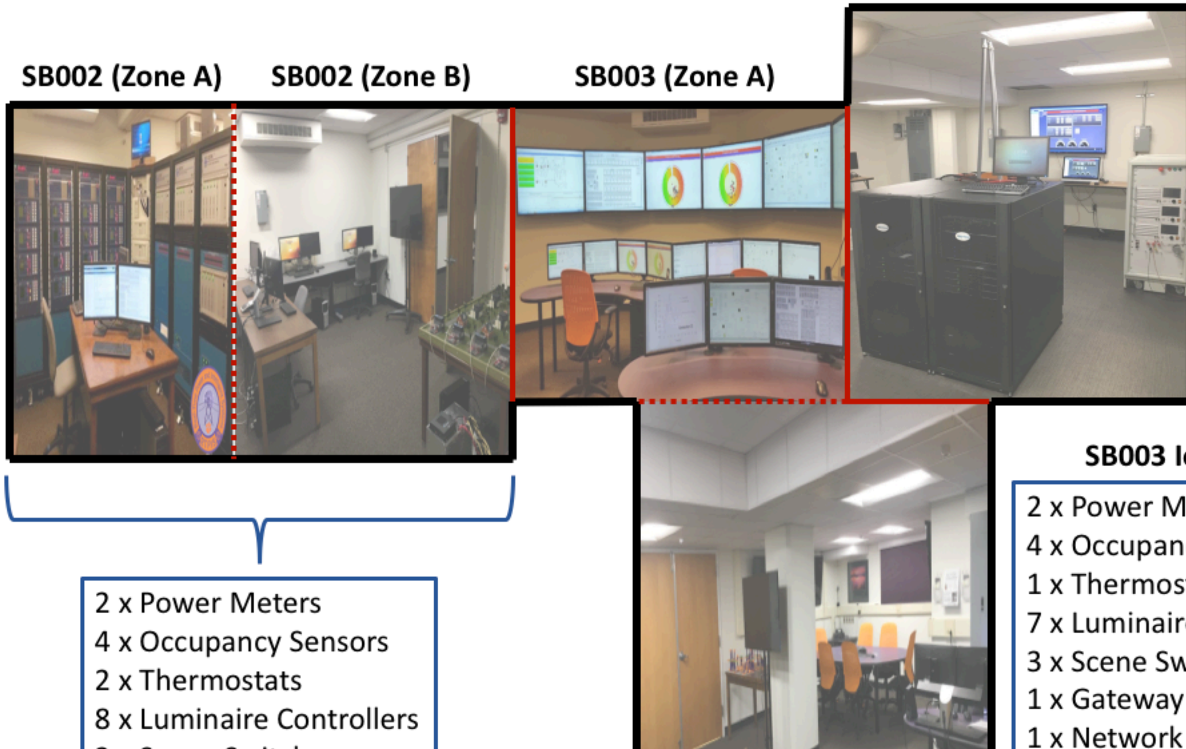
Real-Time Power and Intelligent Systems Laboratory

RTPIS IoT Lab

SB007B

SB002 (Zone A) SB002 (Zone B) SB003 (Zone A)



SB003 (Zone B)

- 1 x Power Meter
- 2 x Occupancy Sensors
- 1 x Thermostat
- 4 x Luminaire Controllers
- 1 x Scene Switch
- 1 x HVAC Unit
- 4 x Light Panels
- 1 x Workstation with IoT Software Platforms

SB007B IoT Devices

SB003 IoT Devices

- 2 x Power Meters
- 4 x Occupancy Sensors
- 1 x Thermostat
- 7 x Luminaire Controllers
- 3 x Scene Switches
- 1 x Gateway
- 1 x Network Control Engine
- 1 x HVAC Unit
- 7 x Light Panels

- 2 x Power Meters
- 4 x Occupancy Sensors
- 2 x Thermostats
- 8 x Luminaire Controllers
- 2 x Scene Switches
- 2 x HVAC Units
- 8 x Light Panels

SB002 IoT Devices

Zone Separation (No Wall Present)

Room Separation (Wall Present)

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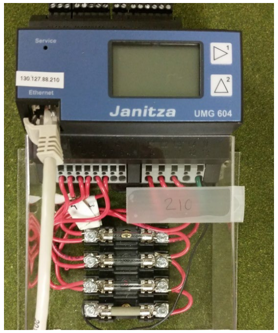
Real-Time Power and Intelligent Systems Laboratory

RTPIS Smart Neighborhood Lab



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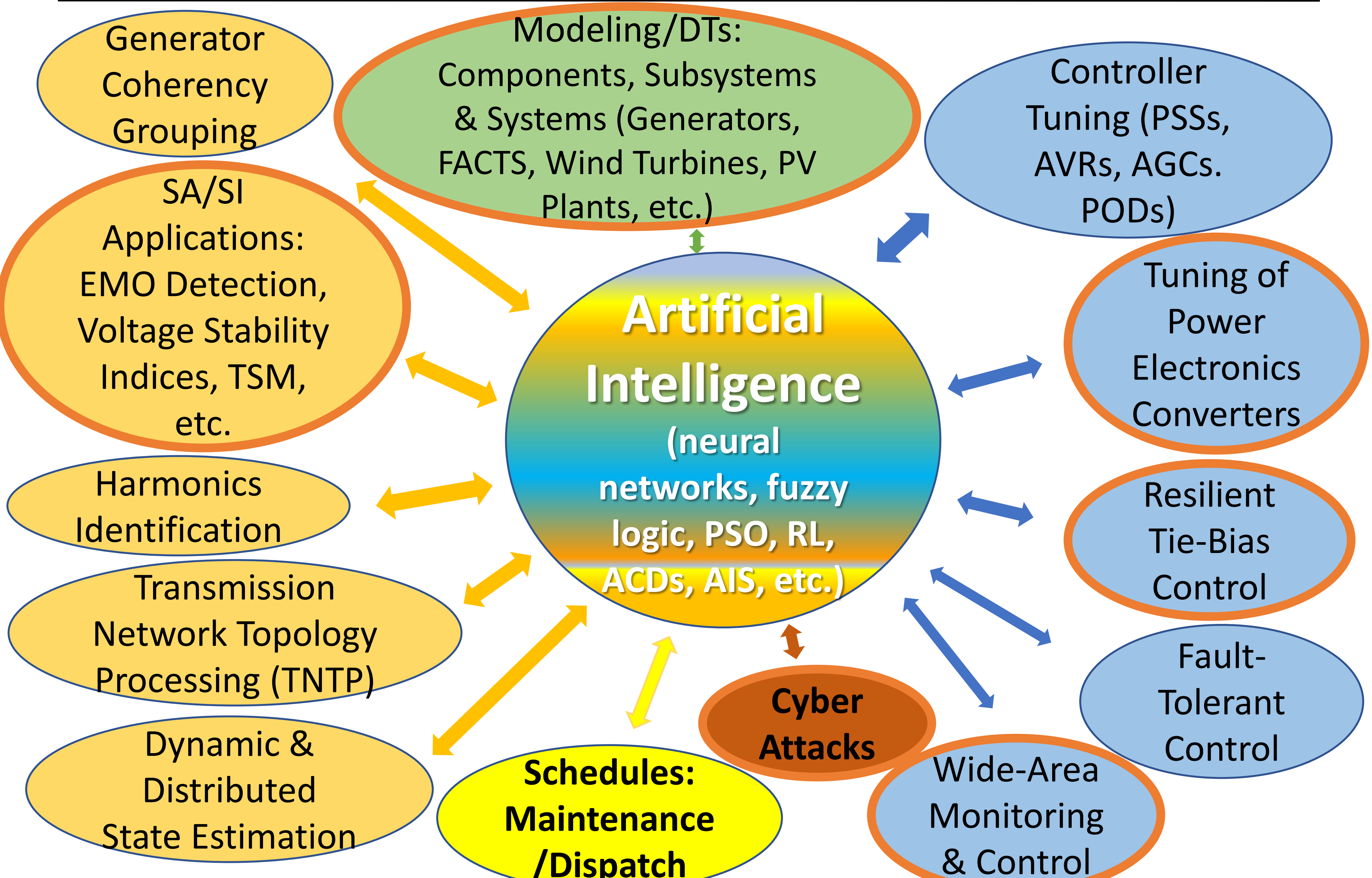
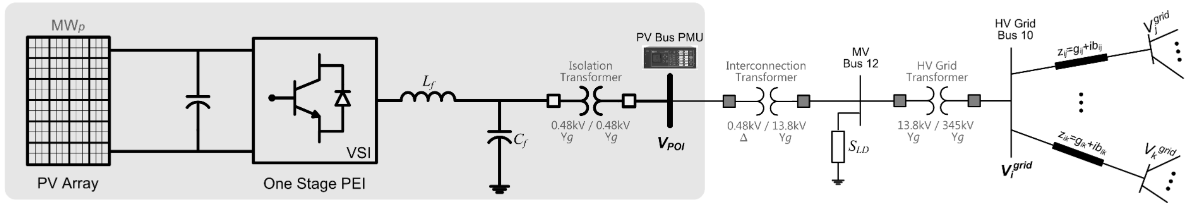
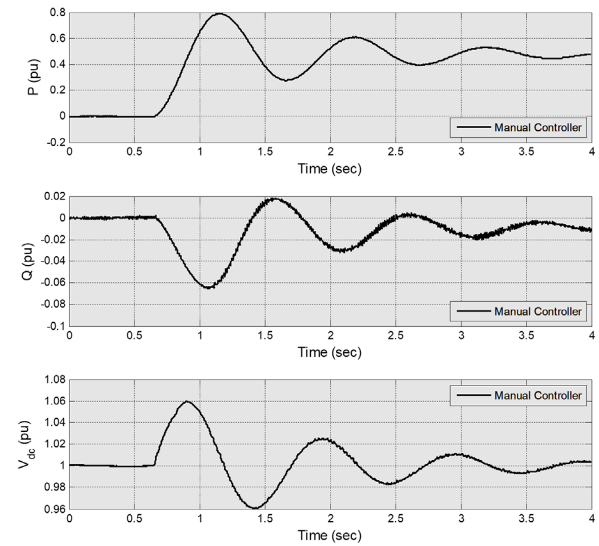


PV Inverter Operation Enhancement



Problem Statement

- Performance of converter-based PV systems primarily depends on its control system. The more optimal the controllers are, the better PEI performance will be
- Very accurate mathematical equations for PEI is difficult to obtain
- Taking into account the complexity, cost, and ineffectuality of conventional tuning methods for systems with increasing number of inverters , the absence of a systematic controller self-tuning approach for PEIs is required.



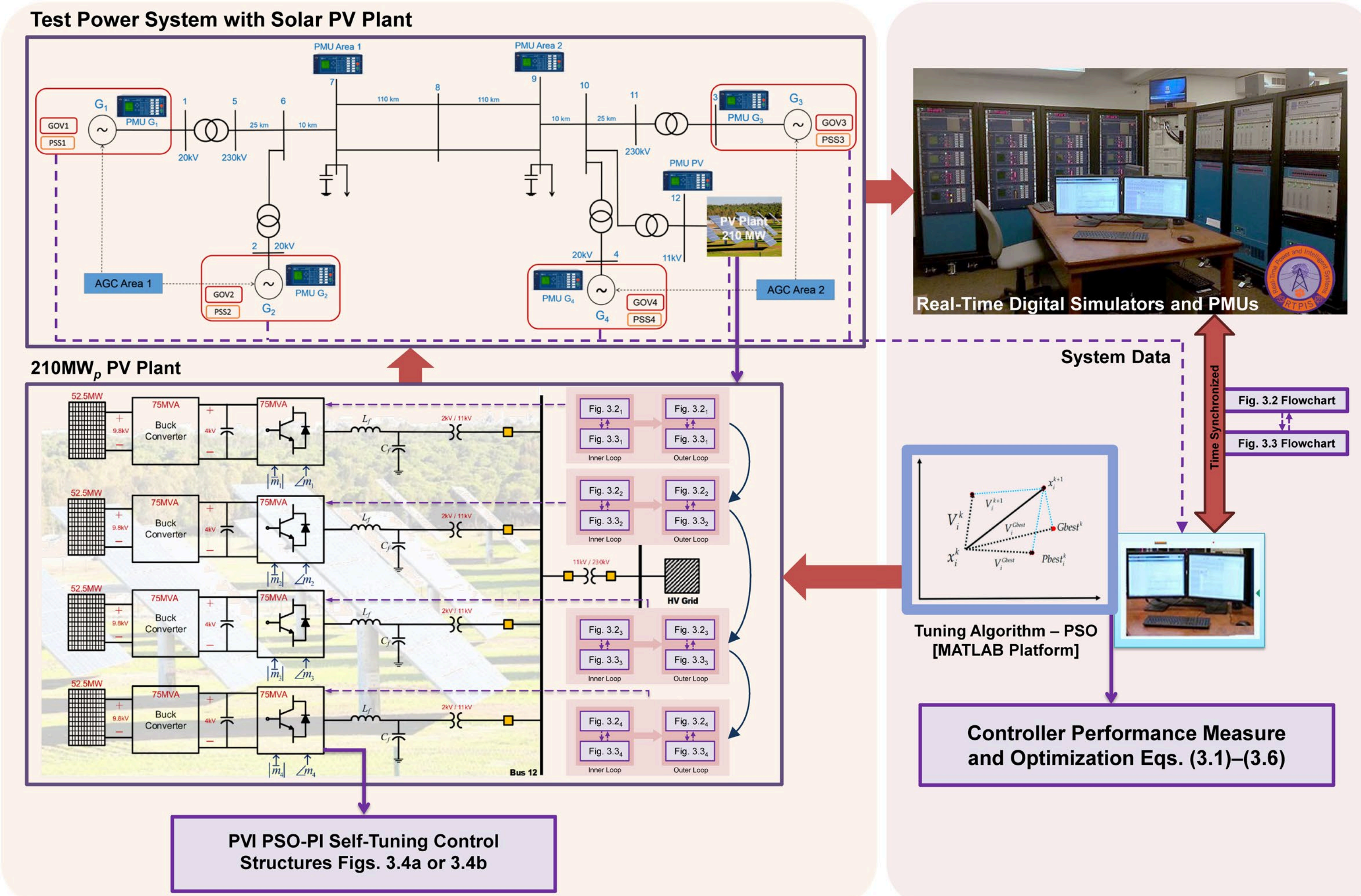
Proposed Solution: Heuristic-Based Controllers for PEIs

- Correct objective function formulation
- Efficient and practical optimization method
- Real-time self-assessment and self-tuning

suitable system dynamic responses

PV Inverter Operation Enhancement

Experimental Platform for Performance Enhancement of Grid-Integrated Photovoltaic Inverters



Arzani A, Venayagamoorthy GK, “Computational Approach to Enhance Performance of Photovoltaic System Inverters Interfaced to Utility Grids”, *IET Renewable Power Generation*, Vol. 12, Issue 1, 2018, pp. 112-124.

PV Inverter Operation Enhancement

$$\min_{J_T^i} \quad J_T^i = \sum_{k=1}^{n}\sum_{j=1}^{m}\left(w_1 J_{\Delta P_{jk}} + w_2 J_{\Delta Q_{jk}}\right)$$

$$\begin{aligned} s.t. \rightarrow \quad & x_n^i(\kappa) \in \mathbb{R} \cap \left[x_{min}(\kappa) \le x_n^i(\kappa) \le x_{max}(\kappa)\right] \\ & \forall i \in \mathbb{Z}^+,\ i = \{1,2,\ldots,20\} \\ & \forall n \in \mathbb{Z}^+,\ n = \{1,2,\ldots,20\} \\ & \forall \kappa \in \mathbb{Z}^+,\ \kappa = \{1,2,3,4\} \end{aligned} \quad (1)$$

$t \epsilon \mathbb{R}^+$	simulation time [sec]
Δt	simulation time step [sec]
t_0	step change instance [sec]
t_2	simulation end time [sec]
$A \epsilon \mathbb{Z}^+$	constant value
$\Delta P, \Delta Q$	alterations in normalized active and reactive power [pu]
$c_p \epsilon \mathbb{R}^+$	constant defined to shift normalized active power waveform steady-state value to zero on horizontal axis; i.e. c_p values used for different solar irradiance step change cases 1, 2, 3 listed in Table 1 are 0.478, 0.23, 0.73, respectively.

$$J_{\Delta P} = \sum_{t=t_0}^{\frac{t_2-t_0}{\Delta t}} \left(\Delta P(t) - c_p\right)^2 \times \left(|A| \times (t - t_0) \times \Delta t\right) \quad (2)$$

$$J_{\Delta Q} = \sum_{t=t_0}^{\frac{t_2-t_0}{\Delta t}} \left(\Delta Q(t)\right)^2 \times \left(|A| \times (t - t_0) \times \Delta t\right) \quad (3)$$

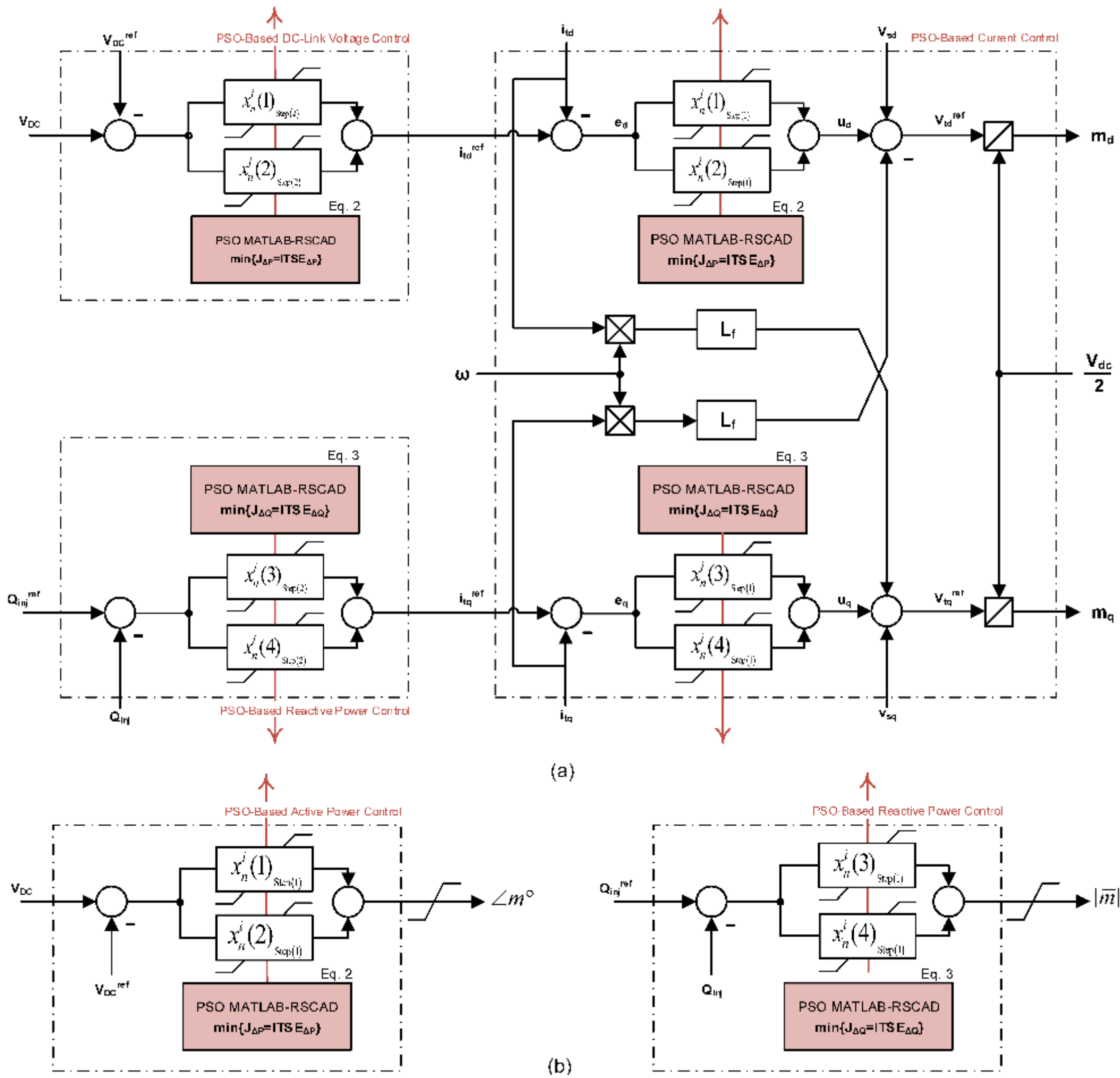
$$x_{gbest}(\kappa) = arg\min_{x_n^i} \left[J_T^i(t),\ x_n^i(\kappa) \in \left[x_{min}(\kappa), x_{max}(\kappa)\right]\right] \quad (4)$$

$$\begin{aligned} x_n^i &= \left\{\forall \kappa \in \mathbb{Z}^+,\ \kappa = [1,d] \mid x_n^i(\kappa) \in \mathbb{R} \subseteq \left[x_{min}(\kappa), x_{max}(\kappa)\right]\right\} \\ &= \left[x_n^i(1) \ldots x_n^i(d)\right] = \left[k_{p1-n}^i, T_{1-n}^i, k_{p2-n}^i, T_{2-n}^i\right] \end{aligned}$$

Arzani A, Venayagamoorthy GK, "Computational Approach to Enhance Performance of Photovoltaic System Inverters Interfaced to Utility Grids", *IET Renewable Power Generation*, Vol. 12, Issue 1, 2018, pp. 112-124.

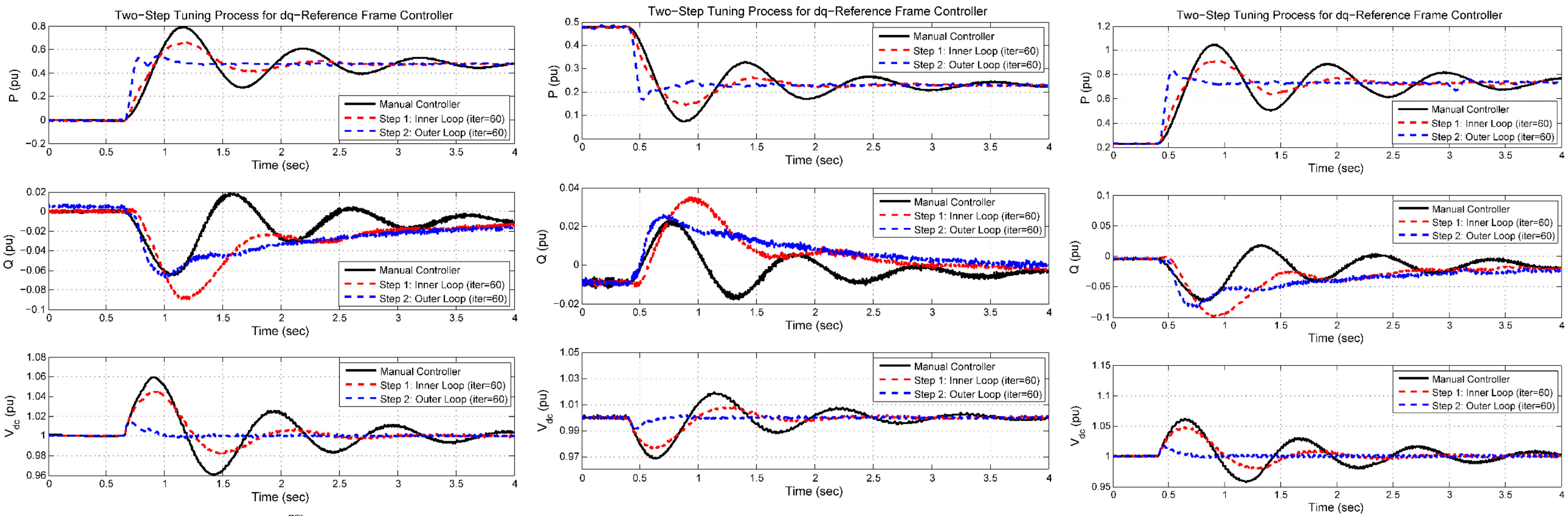
PV Inverter Operation Enhancement

- Tuning of all parameters of the two PV-inverter controller structures has been accomplished utilizing PSO in a number of steps
- This **multi-step tuning process** continues till that last PVI has been optimally tuned
- The final result is the optimal-tuning of all PV-inverters' controllers, enhancing the PV plant's transient and steady-state step-response performance over a wide irradiance operating range



PSO-Based PVI Control Structures

PV Inverter Operation Enhancement



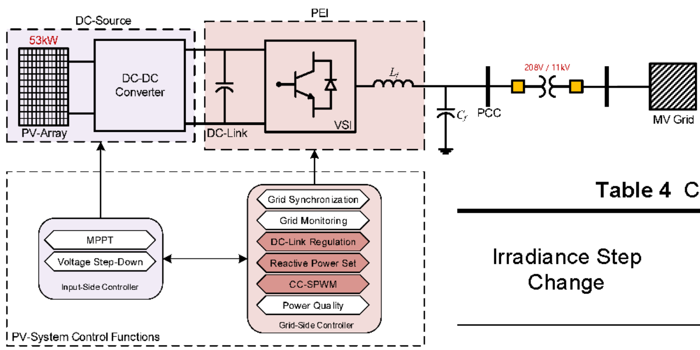


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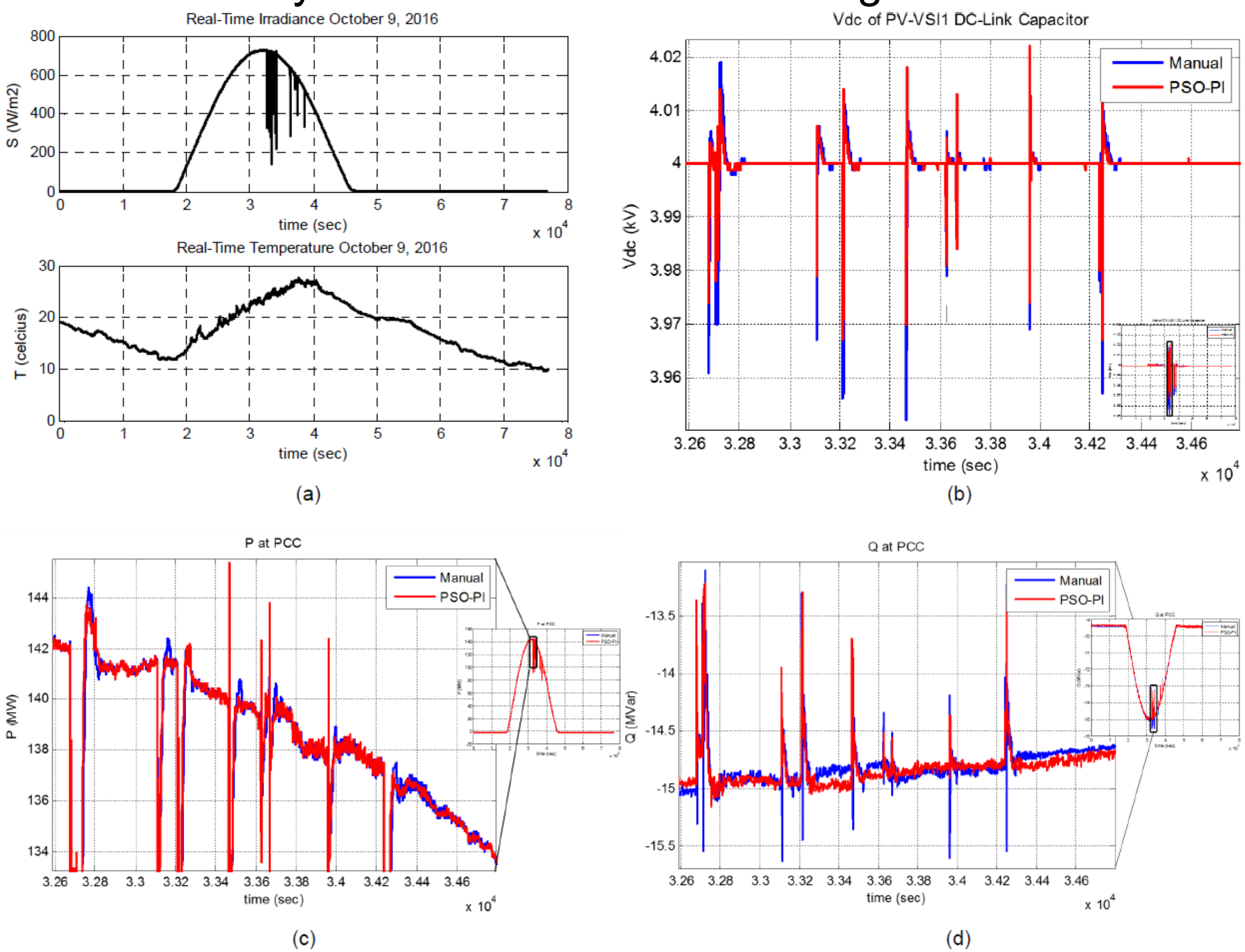
Table 4 Commercial PV System Step-Response Performance Specification for Two Types of PV-VSI Controllers

Irradiance Step Change	Controller Type	Active Power (pu)				DC-Voltage (pu)			
		P_{peak}	P_{ss}	M_P (%)	t_{ss} (sec)	Vdc_{peak}	Vdc_{SS}	M_{Vdc} (%)	t_{ss} (sec)
0 to 500 (W/m^2)	Manual	0.7916	0.4836	63.69	3.199	1.0594	0.9999	5.9504	2.478
	Step 1	0.6605	0.4772	38.40	1.694	1.0450	1.0001	4.4945	1.118
	Step 2	0.5474	0.4772	14.71	0.424	1.0140	1.0000	1.4029	0.156
500 to 250 (W/m^2)	Manual	0.0735	0.2290	-67.59	3.192	0.9685	1.0004	-3.19	1.914
	Step 1	0.1447	0.2290	-36.29	1.798	0.9765	0.9999	-2.34	1.029
	Step 2	0.1655	0.2293	-26.82	0.344	0.9912	1.0000	-1.08	0.152
250 to 750 (W/m^2)	Manual	1.0460	0.7290	43.49	4.000	1.0619	0.9987	6.33	3.700
	Step 1	0.9171	0.7314	25.39	1.275	1.0478	1.0003	4.75	1.547
	Step 2	0.8321	0.7319	13.68	0.232	1.0171	1.0000	1.71	0.184

PV Inverter Operation Enhancement

Dynamic Responses to Real-Time Weather at Clemson

- Weather profile measured from the weather monitoring station at Clemson University
- Results verify the effectiveness of utilizing heuristic-tuned PVI controllers



(a) 24 hours weather profile, **(b)** Real-time dc-Link voltage of PVI1 with manual- and heuristic-tuned controllers, **(c)** Real-time active power at PCC with PVI manual- and heuristic-tuned controllers, **(d)** Real-time reactive power at PCC with PVI manual- and heuristic-tuned controllers

Arzani A, Venayagamoorthy GK, "Computational Approach to Enhance Performance of Photovoltaic System Inverters Interfaced to Utility Grids", *IET Renewable Power Generation*, Vol. 12, Issue 1, 2018, pp. 112-124.

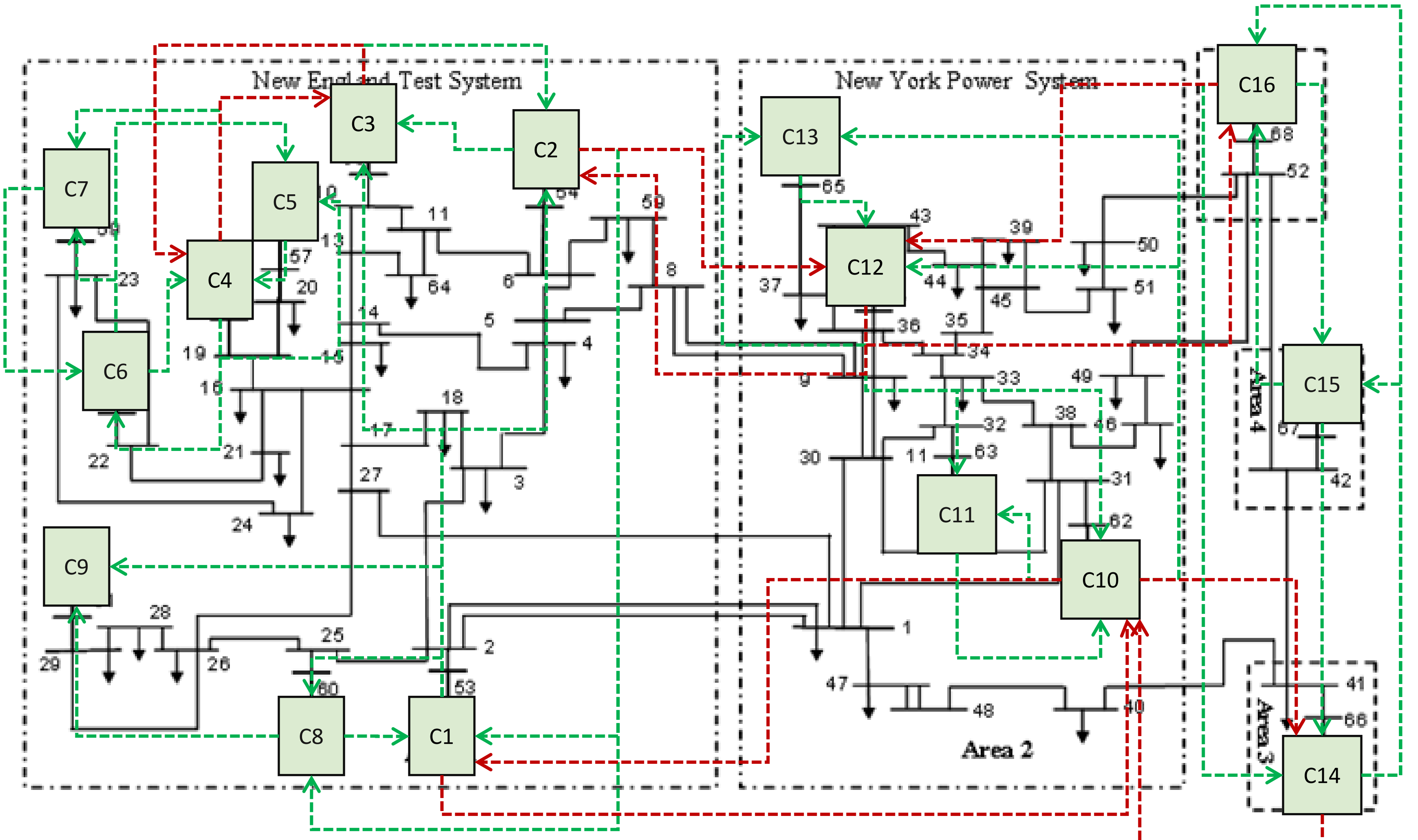
PV Inverter Operation Enhancement

$\Delta S = +500 W/m^2$	Manual-Tuned $T.E_{PV}^{M}\left[kWsec\right]$	Heuristic-Tuned $T.E_{PV}^{H}\left[kWsec\right]$	$\Delta T.E_{PV}\left[kWsec\right]$ Savings	Performance Improvement	$T.E_{PV}^{H} \Big/ \sum_{t=t_r^{min}}^{t=t_{ss}^{max}} (P_{base} \cdot t)$
Commercial PV System	14.03	1.34	12.7	90.47%	0.63%
Utility-Scale PV Plant	51030	14007	37023	72.55%	0.67%

- *T.E.* reduced substantially for both commercial and utility PV systems.
- *T.E. r*esults indicate that more tuning intelligence is required for large number of small PV systems compared to the same aggregate in size small number of large PV systems.
- Very close percentage values in the last column indicate consistency.

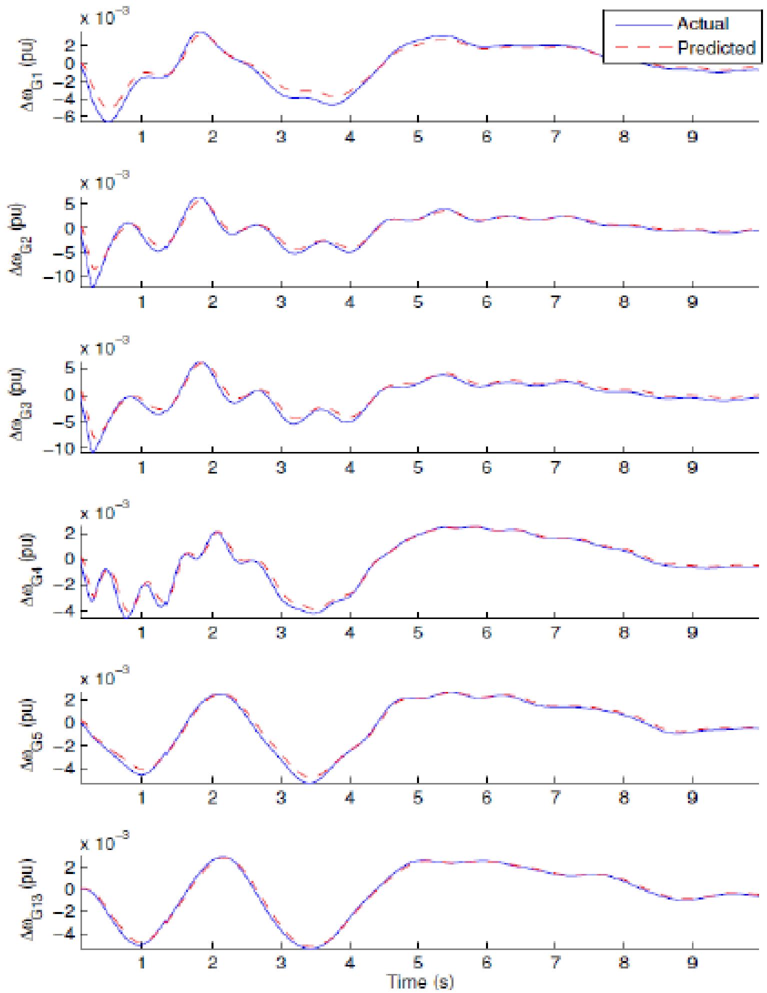
Arzani A, Venayagamoorthy GK, "Computational Approach to Enhance Performance of Photovoltaic System Inverters Interfaced to Utility Grids", *IET Renewable Power Generation*, Vol. 12, Issue 1, 2018, pp. 112-124.

Scalable Online CCN for Identification/Estimation/Prediction



Luitel B, Venayagamoorthy GK, "Decentralized Asynchronous Learning in Cellular Neural Networks", *IEEE Transactions on Neural Networks*, November 2012, vol. 23. no. 11, pp. 1755-1766,

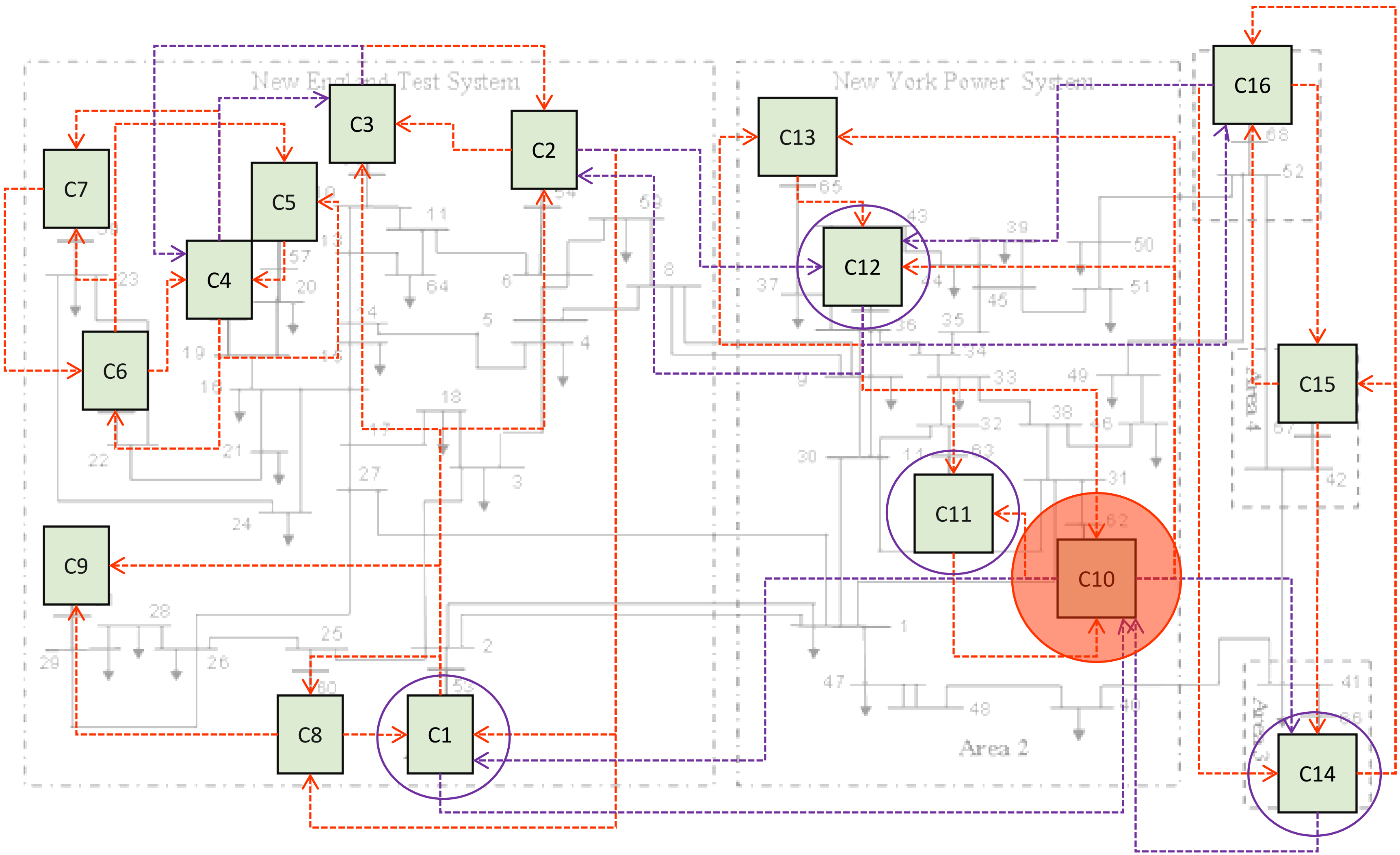
CCN based Power System Model



Hz	%	G3	Hz	%
0.1728	1		0.1409	1
0.2594	0.0549		0.2625	0.0677
0.2594	0.0549		0.2625	0.0677
0.6659	-0.0071		0.5862	1
0.6659	-0.0071		0.6675	-0.0169
0.8357	1		0.6675	-0.0169
1.0866	0.0382		1.1102	0.0497
1.0866	0.0382		1.1102	0.0497
1.5552	0.0614		1.5753	0.0455
1.5552	0.0614		1.5753	0.0455

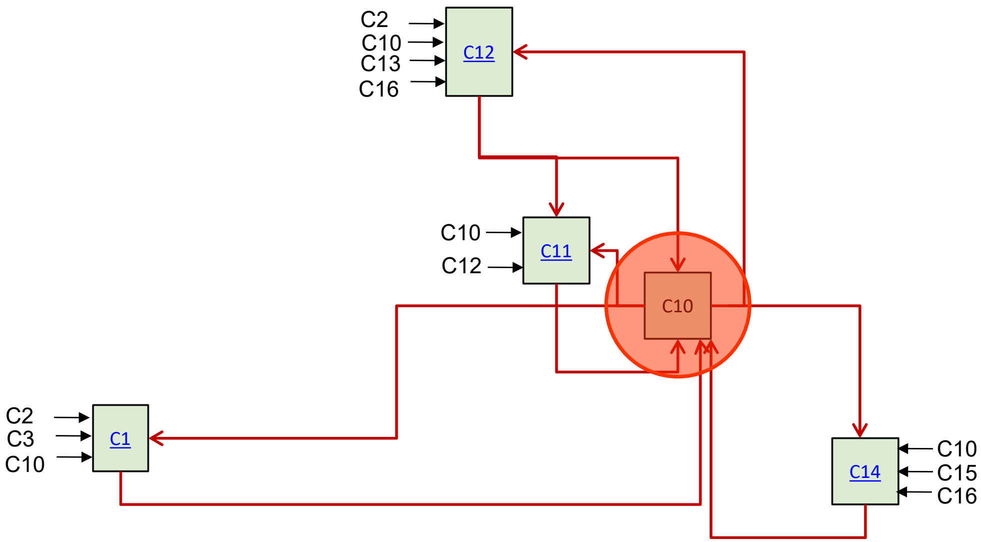
Venayagamoorthy GK, "Computational Approaches for Bad Data Handling in Power System Synchrophasor Networks", *19th World Congress of the International Federation of Automatic Control*, Cape Town, South Africa, August 24-29, 2014, pp. 11269-11274

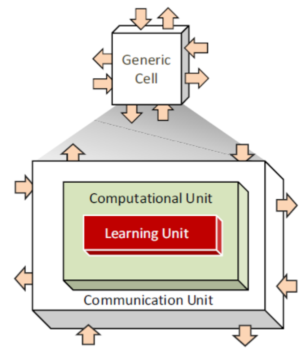
CCN: speedNet

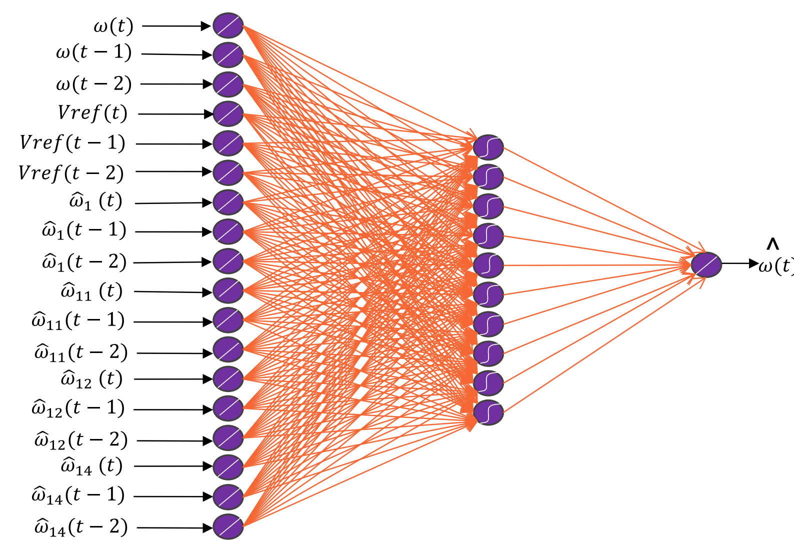


Venayagamoorthy GK, "Computational Approaches for Bad Data Handling in Power System Synchrophasor Networks", *19th World Congress of the International Federation of Automatic Control*, Cape Town, South Africa, August 24-29, 2014, pp. 11269-11274

Computational Network for Generator G10

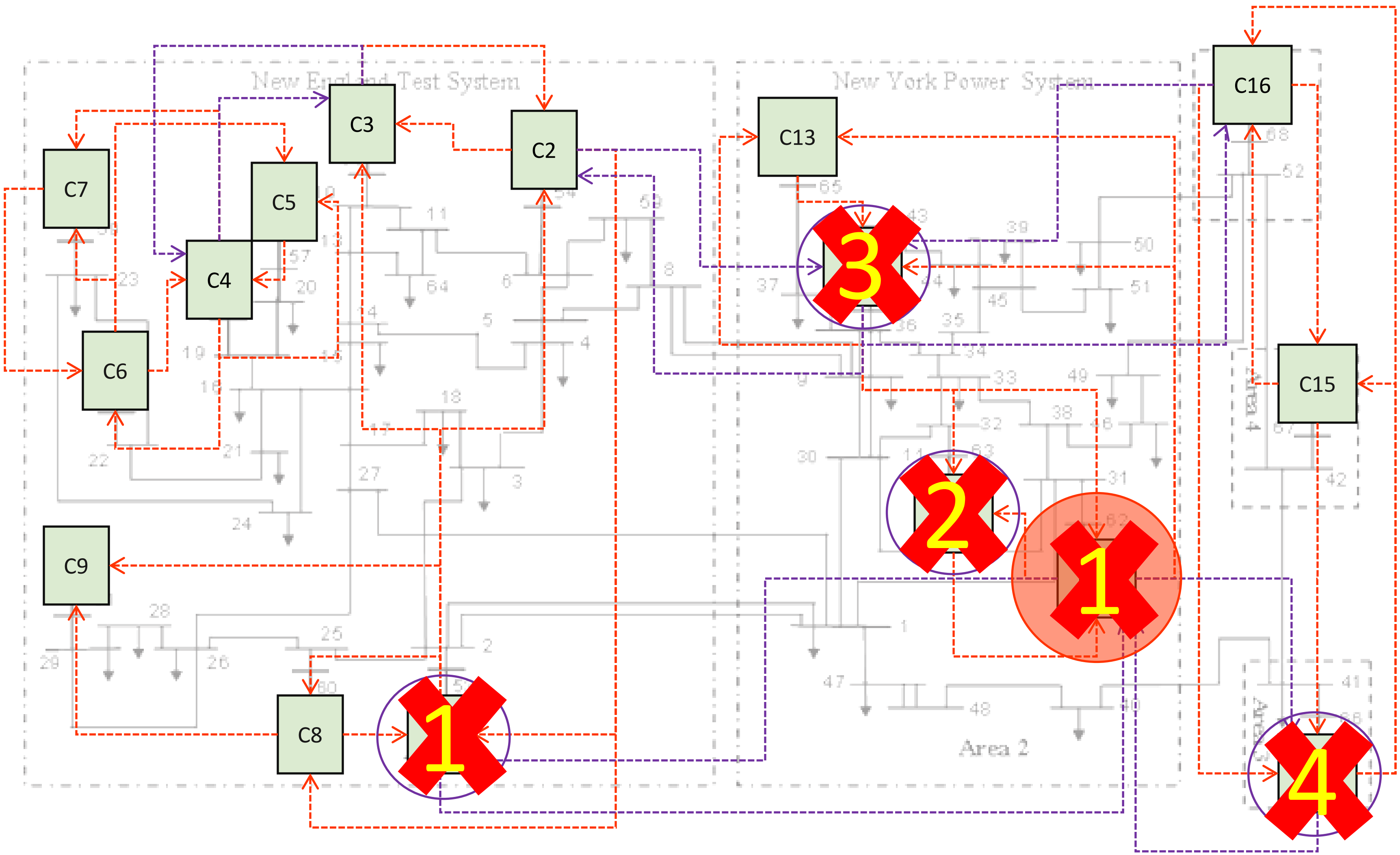






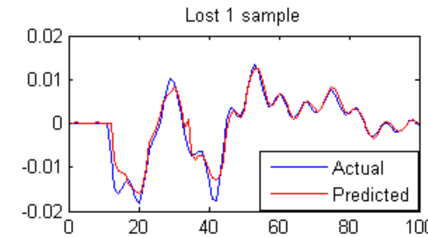
Venayagamoorthy GK, "Computational Approaches for Bad Data Handling in Power System Synchrophasor Networks", *19th World Congress of the International Federation of Automatic Control*, Cape Town, South Africa, August 24-29, 2014, pp. 11269-11274

CCN: speedNet



Venayagamoorthy GK, “Computational Approaches for Bad Data Handling in Power System Synchrophasor Networks”, *19th World Congress of the International Federation of Automatic Control*, Cape Town, South Africa, August 24-29, 2014, pp. 11269-11274

Virtual IoTs



Cells: 10, 1

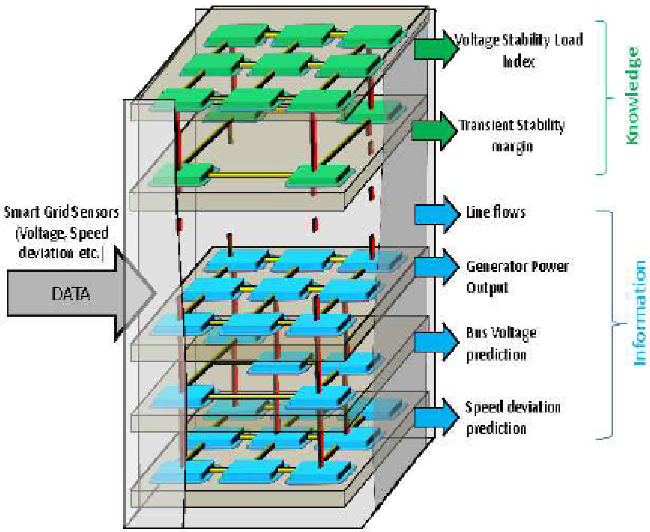
Cells: 10, 1, 11

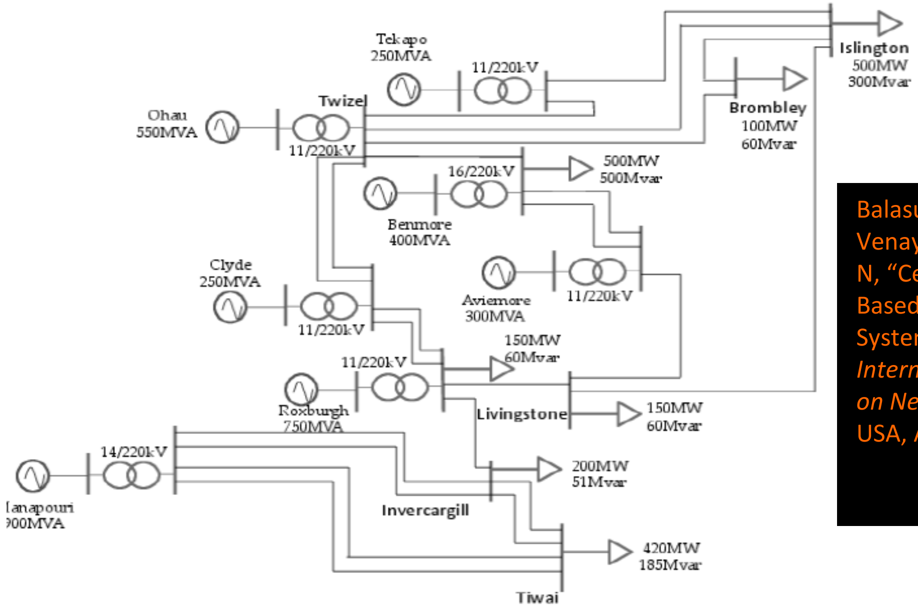
Cells: 10, 1, 11, 12

Cells: 10, 1, 11, 12, 14

Venayagamoorthy GK, "Computational Approaches for Bad Data Handling in Power System Synchrophasor Networks", *19th World Congress of the International Federation of Automatic Control*, Cape Town, South Africa, August 24-29, 2014, pp. 11269-11274

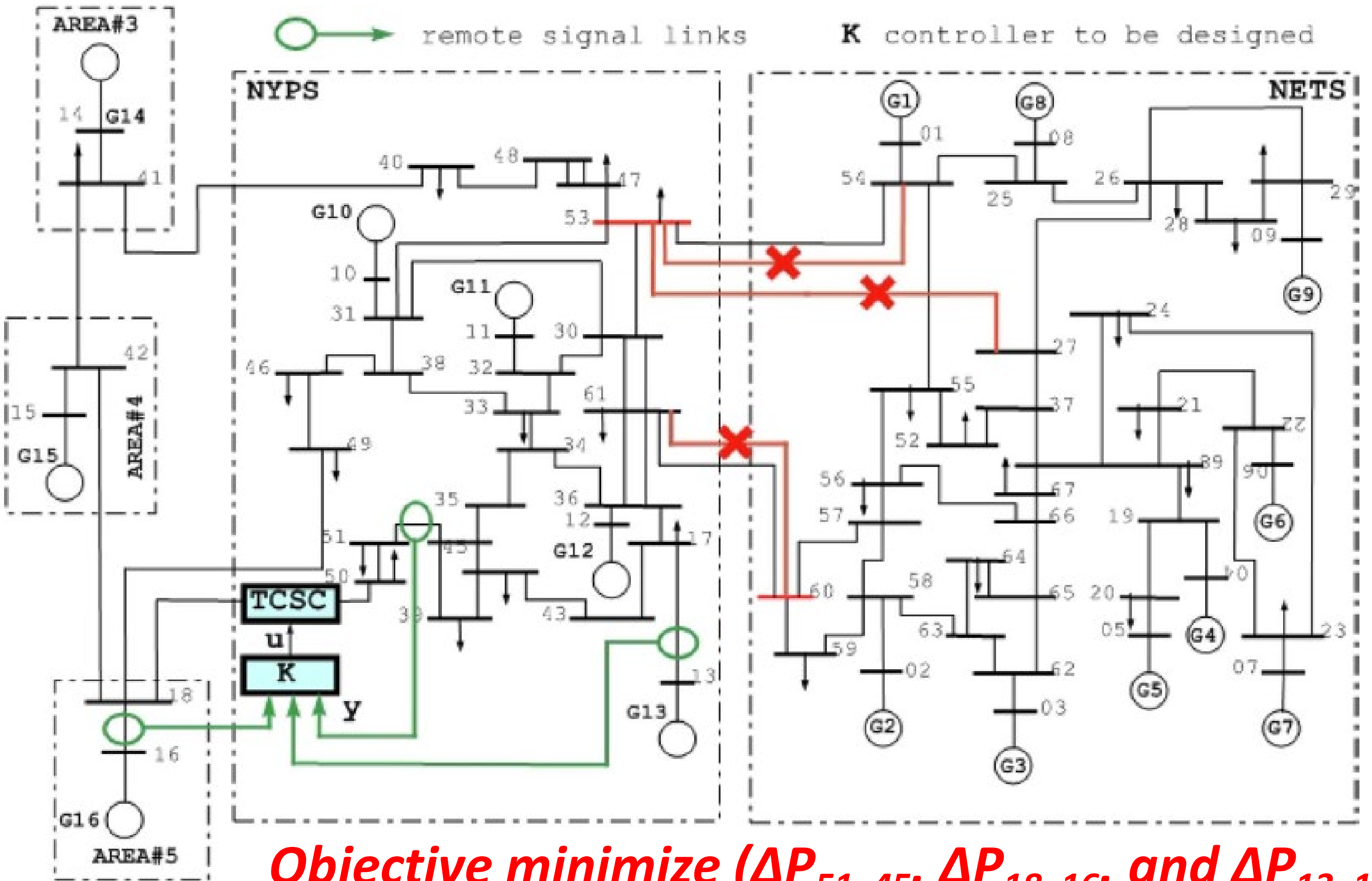
Situational Intelligence





Balasubramaniam K, Venayagamoorthy GK, Watson N, "Cellular Neural Network Based Situational Awareness System for Power Grids", *IEEE International Joint Conference on Neural Networks*, Dallas, TX, USA, August 4-9, 2013

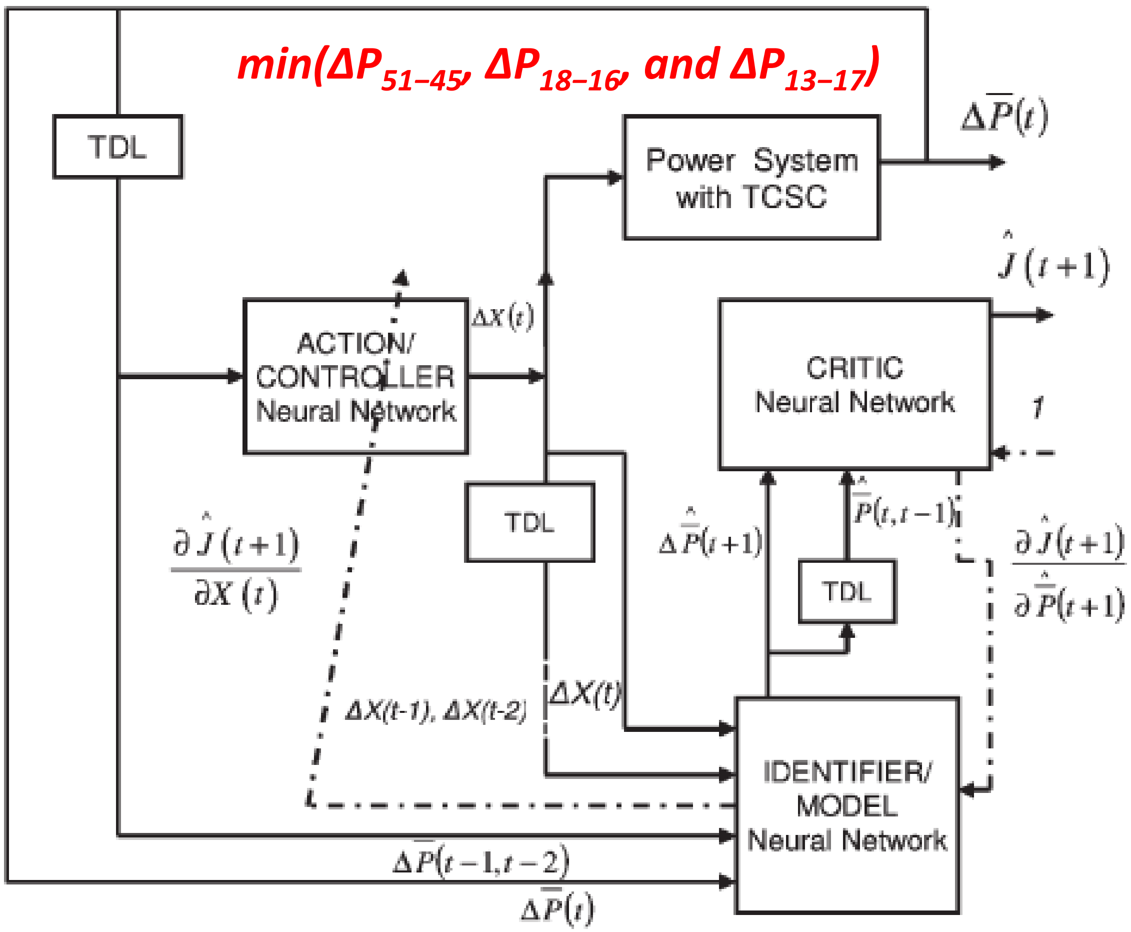
Adaptive Critic-Based WAC



Objective minimize (ΔP_{51-45}, ΔP_{18-16}, and ΔP_{13-17})

Ray S, Venayagamoorthy GK, Chaudhuri B, Majumder R, "Comparison of Adaptive Critics and Classical Approaches Based Wide Area Controllers for a Power System", IEEE Transactions on System, Man and Cybernetics, Part B: Cybernetics, Vol. 38, No. 4, August 2008, pp. 1002-1007.

Adaptive Critic-Based WAC

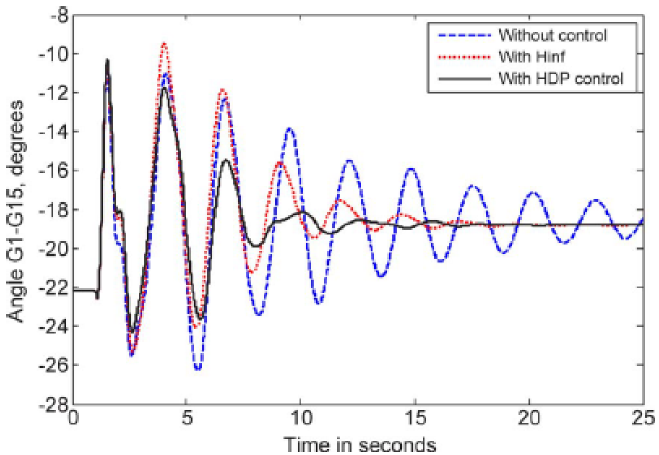


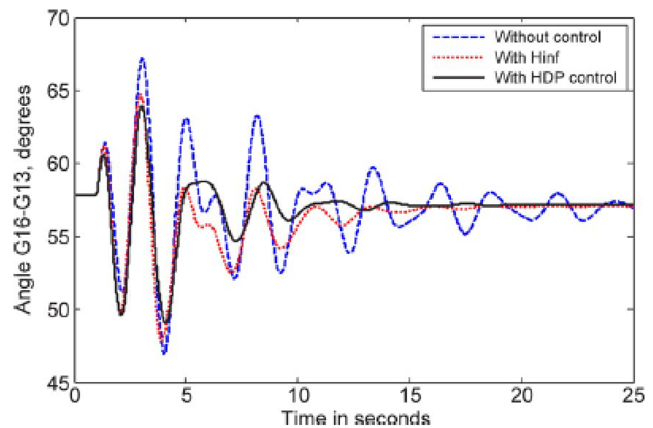
$$
\begin{aligned}
J(t) &= \sum_{k=0}^{\infty} \gamma^k U(t+k) \\
&= U(t) + \sum_{k=1}^{\infty} \gamma^k U(t+k) \\
&= U(t) + \gamma \sum_{k=0}^{\infty} \gamma^k U((t+1)+k) \\
&= U(t) + \gamma J(t+1).
\end{aligned}
$$

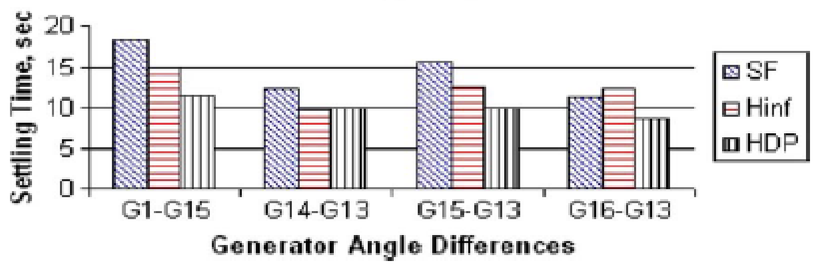
Ray S, Venayagamoorthy GK, Chaudhuri B, Majumder R, "Comparison of Adaptive Critics and Classical Approaches Based Wide Area Controllers for a Power System", IEEE Transactions on System, Man and Cybernetics, Part B: Cybernetics, Vol. 38, No. 4, August 2008, pp. 1002-1007

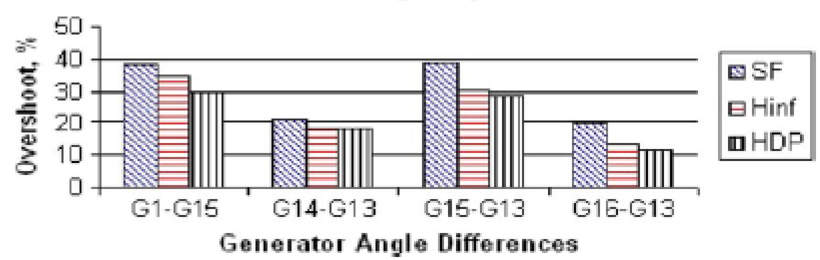
Adaptive Critic-Based WAC

Contingency: A 3-Φ line to ground fault at bus 53 for 80 ms and cleared by permanently opening lines 27–53 thereby changing the postfault topology of the power system.







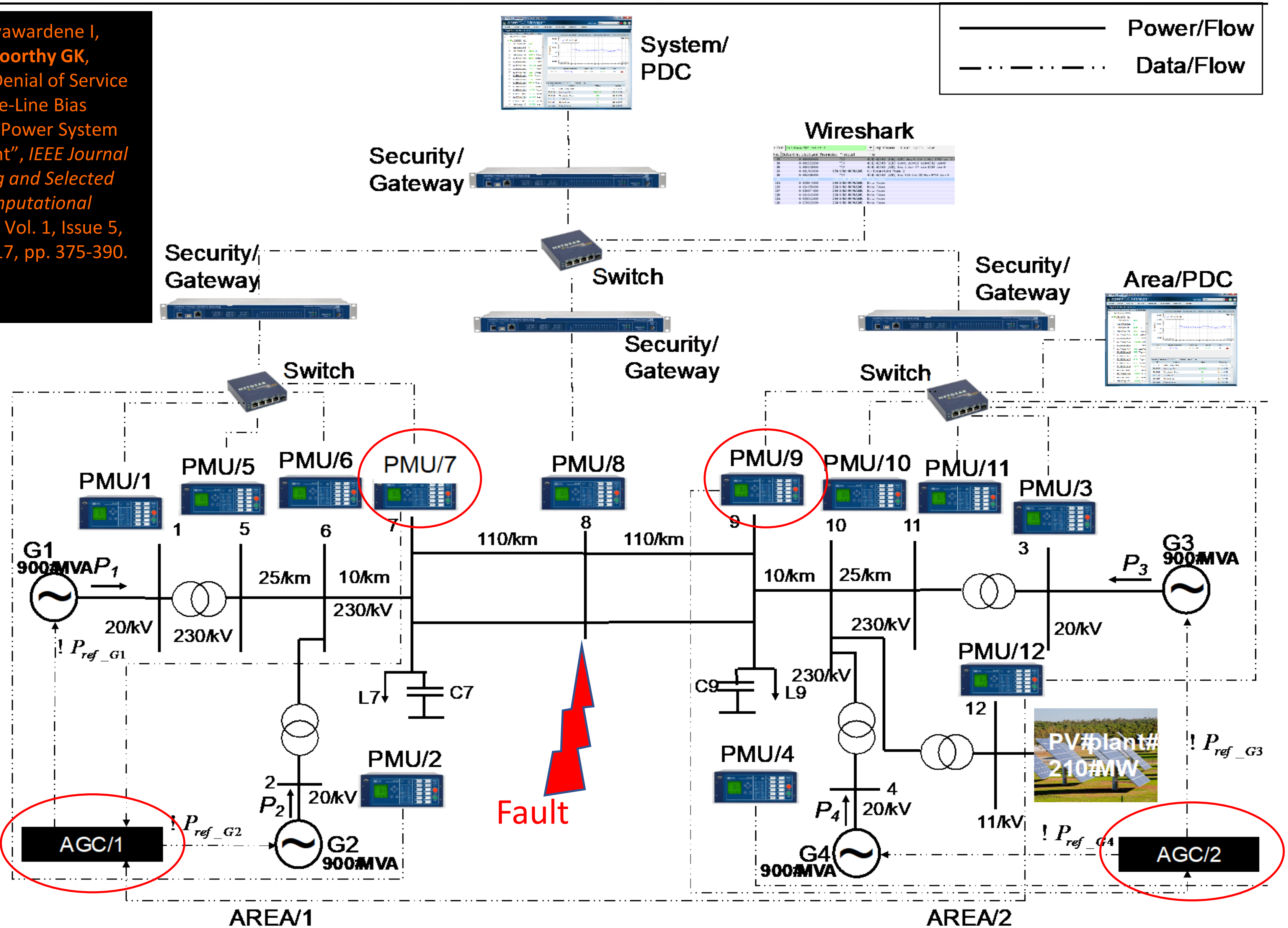


State Feedback		H^{∞}		HDP	
Freq. (Hz)	Damping Ratio	Freq. (Hz)	Damping Ratio	Freq. (Hz)	Damping Ratio
0.3948	0.1617	0.3913	0.1681	0.3720	0.2067
0.5394	0.1412	0.4964	0.1410	0.4850	0.1244
0.7435	0.0679	0.6344	0.1154	0.5898	0.1235

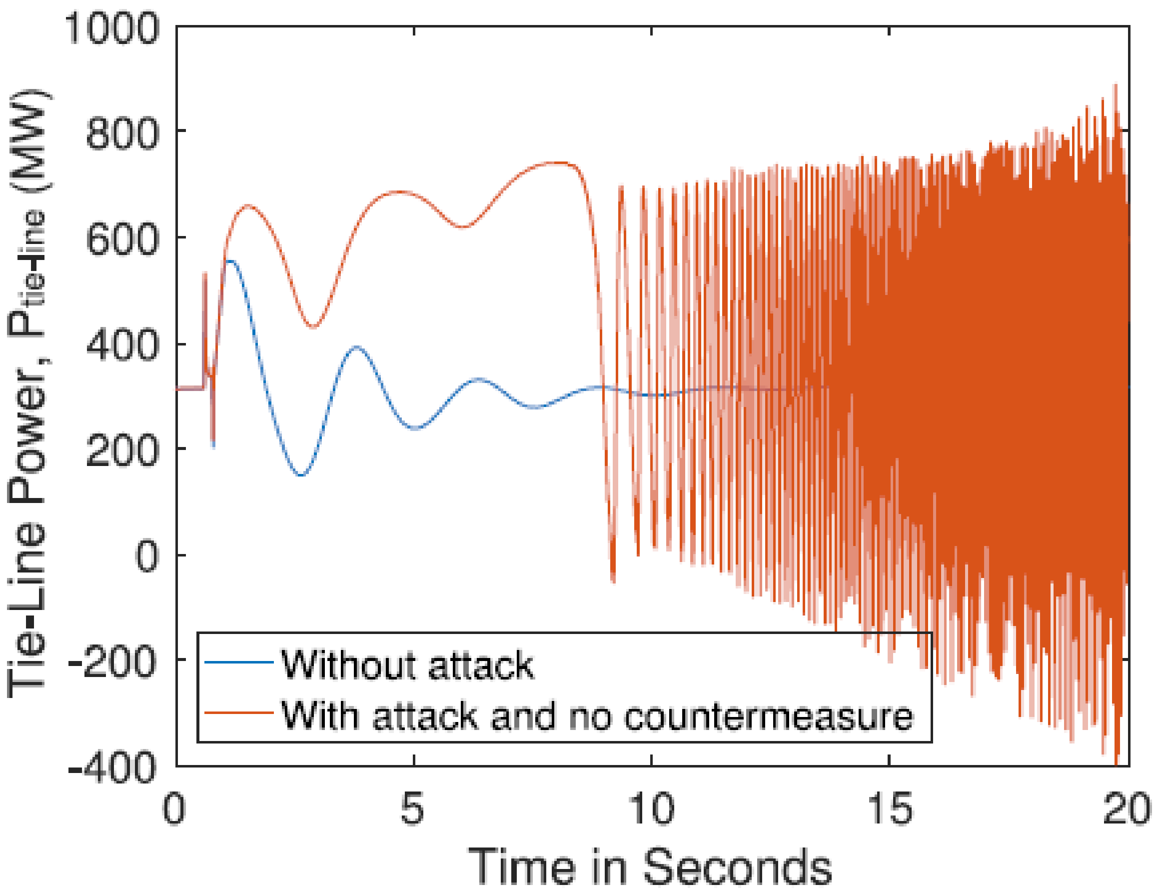
Ray S, Venayagamoorthy GK, Chaudhuri B, Majumder R, "Comparison of Adaptive Critics and Classical Approaches Based Wide Area Controllers for a Power System", IEEE Transactions on System, Man and Cybernetics, Part B: Cybernetics, Vol. 38, No. 4, August 2008, pp. 1002-1007

Multiple Layered DoS Attacks

Zhong X, Jayawardene I, **Venayagamoorthy GK**, Brooks R, “Denial of Service Attack on Tie-Line Bias Control in a Power System with PV Plant”, *IEEE Journal on Emerging and Selected Topic in Computational Intelligence*, Vol. 1, Issue 5, October 2017, pp. 375-390.



DoS on PMU: 100 Packets Blocked



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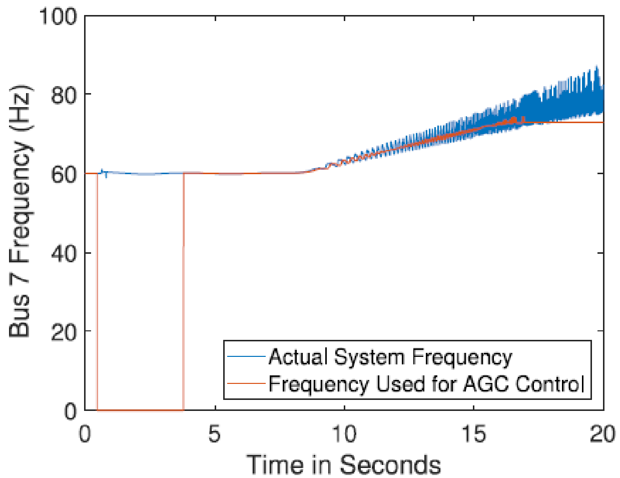
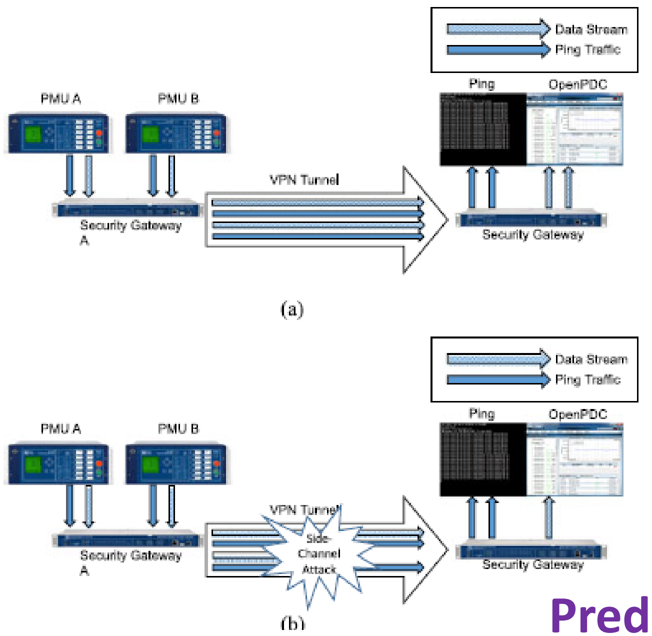
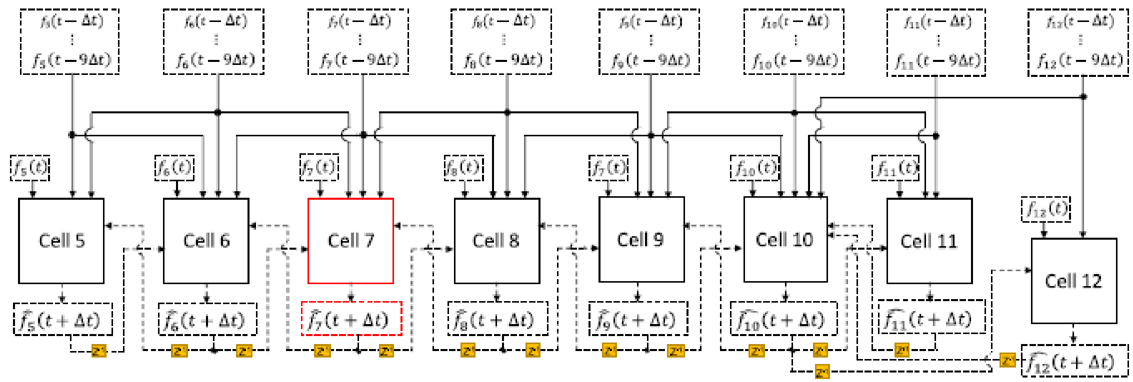


Denial of Service Attacks

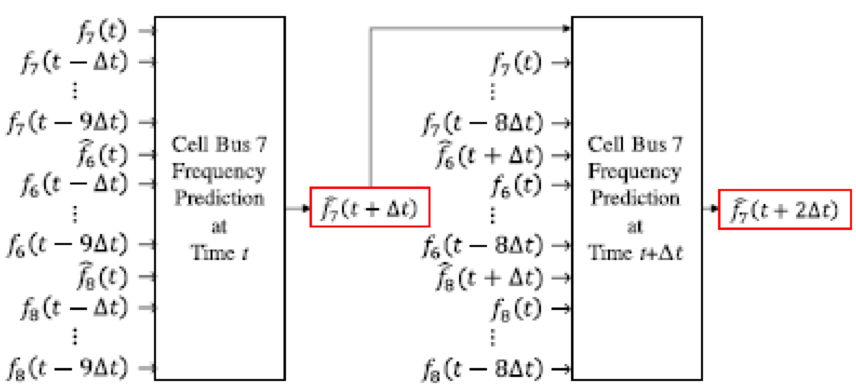
Synchrophasor Network

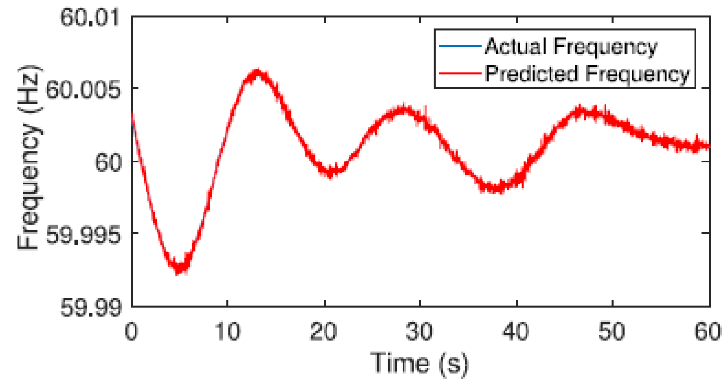


Distributed AI



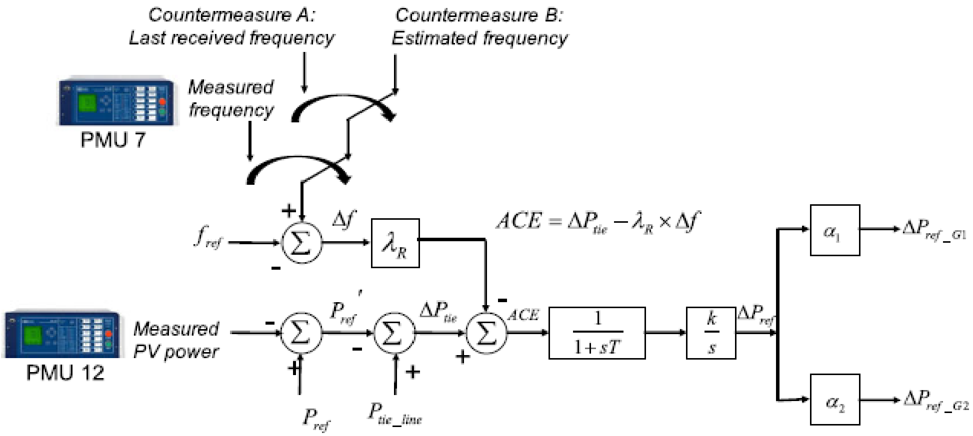
Predictive Estimation of Bus Frequency

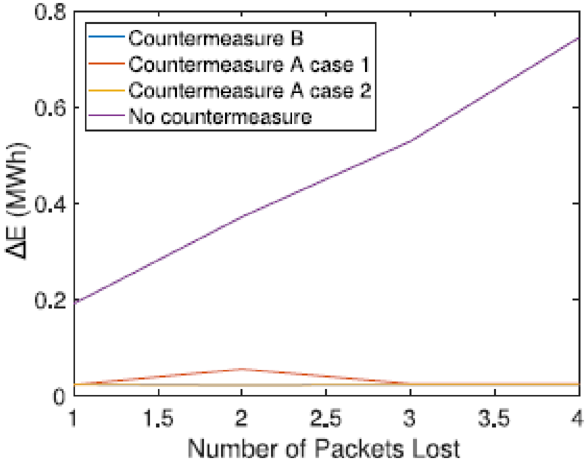




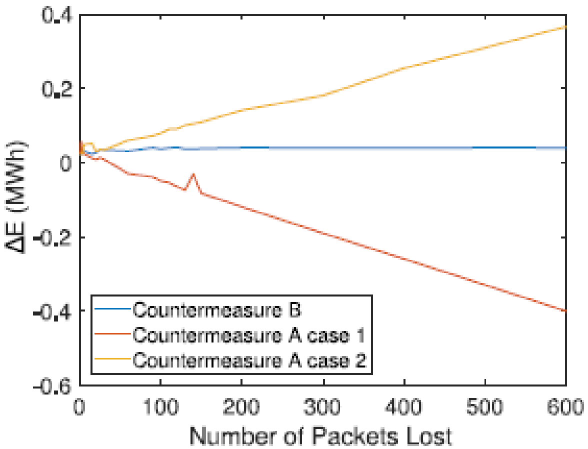
Zhong X, Jayawardene I, Venayagamoorthy GK, Brooks R, "Denial of Service Attack on Tie-Line Bias Control in a Power System with PV Plant", *IEEE Transactions on Emerging Topics in Computational Intelligence*, Vol. 1, Issue 5, October 2017, pp. 375-390.

DoS Attack – Tie-Line Energy Change





(a)

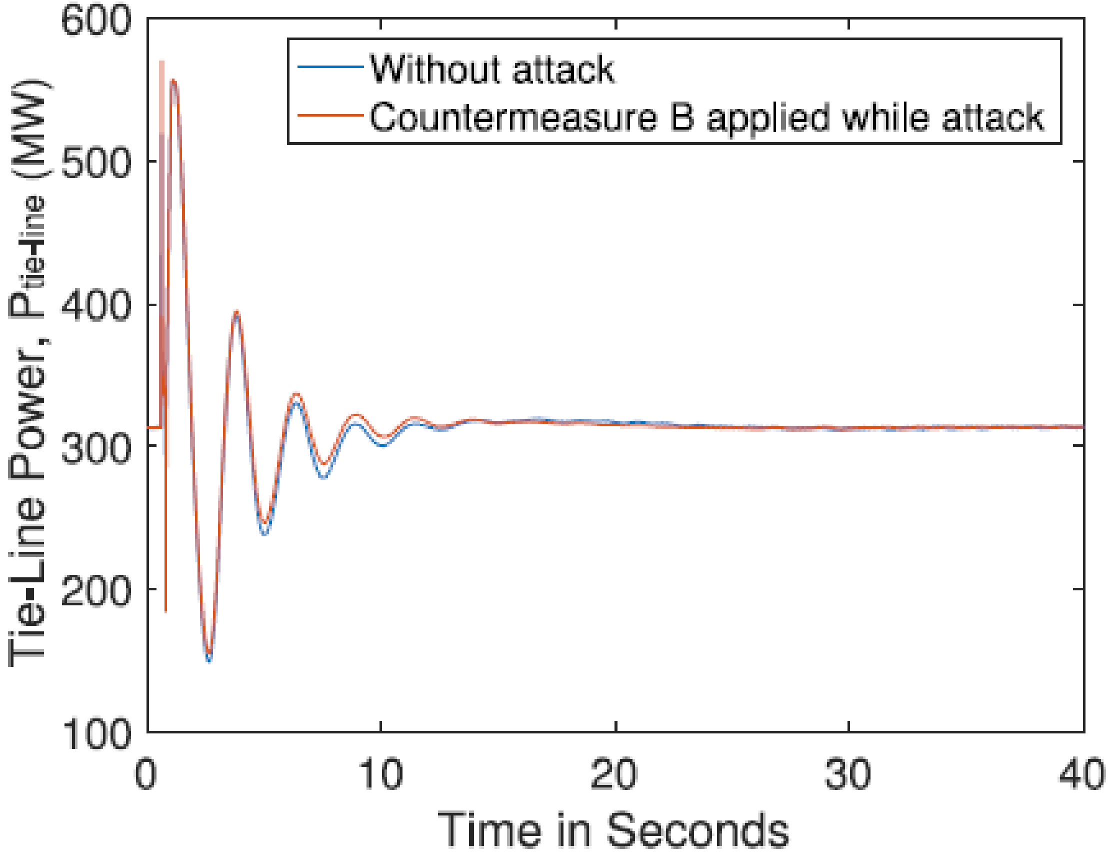


(b)

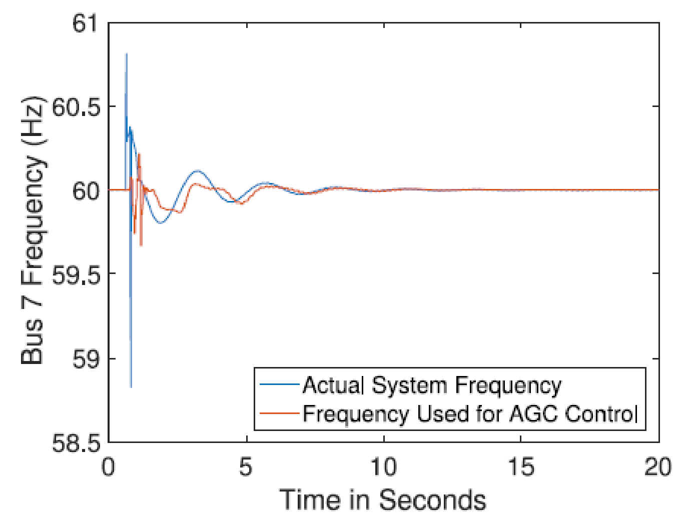
Zhong X, Jayawardene I, Venayagamoorthy GK, Brooks R, “Denial of Service Attack on Tie-Line Bias Control in a Power System with PV Plant”, *IEEE Transactions on Emerging Topics in Computational Intelligence,* Vol. 1, Issue 5, October 2017, pp. 375-390.

Denial of Service Attacks

300 Packets Blocked by an Attacker



Distributed AI in Action



Zhong X, Jayawardene I, Venayagamoorthy GK, Brooks R, "Denial of Service Attack on Tie-Line Bias Control in a Power System with PV Plant", *IEEE Transactions on Emerging Topics in Computational Intelligence,* Vol. 1, Issue 5, October 2017, pp. 375-390.

Outline

- Introduction
- Artificial Intelligence
- RTPIS Lab
- Selected Case Studies
- Summary

Summary

- Threading artificial intelligence into control, operations and management is inevitable for realizing resilient, sustainable and secure transformative power and energy systems.

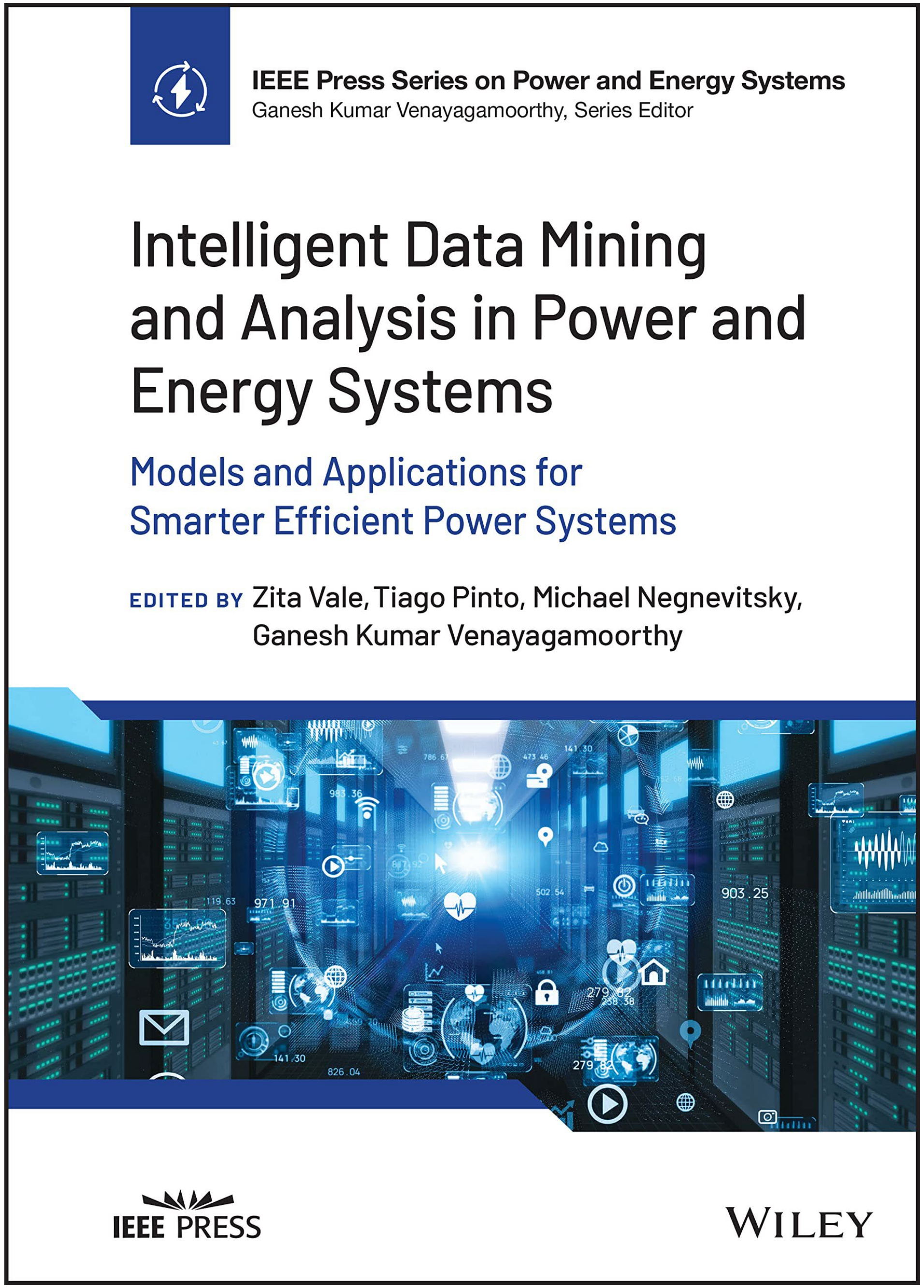
- Real-time simulations accelerates AI research, education and innovation for resilient, sustainable and secure power and energy systems.

- The future resides in Quantum-AI and faster than real-time power and energy systems simulation on quantum computers.

Venayagamoorthy GK, “Future Grids will not be Controllable without Thinking Machines”, *IEEE Smart Grid Newsletter* – (letter), October 2011.

Venayagamoorthy GK, "Dynamic, Stochastic, Computational, and Scalable Technologies for Smart Grids," IEEE Computational Intelligence Magazine, vol.6, no.3, pp.22-35, Aug. 2011.

Venayagamoorthy GK, “Potentials and Promises of Computational Intelligence for Smart Grids”, *IEEE Power General Society General Meeting,* Calgary, AB, Canada, July 26-30, 2009, pp. 1-6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Thank You!

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PhD, MBA, FIEEE, FIET, FSAIEE & FAAIA
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Duke Energy Distinguished Profesor of Power Engineering and Professor of Electrical and Computer Engineering
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May 16th, 2023