Scalable Monitoring and DSOPF Control for Smart Grids

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Introduction

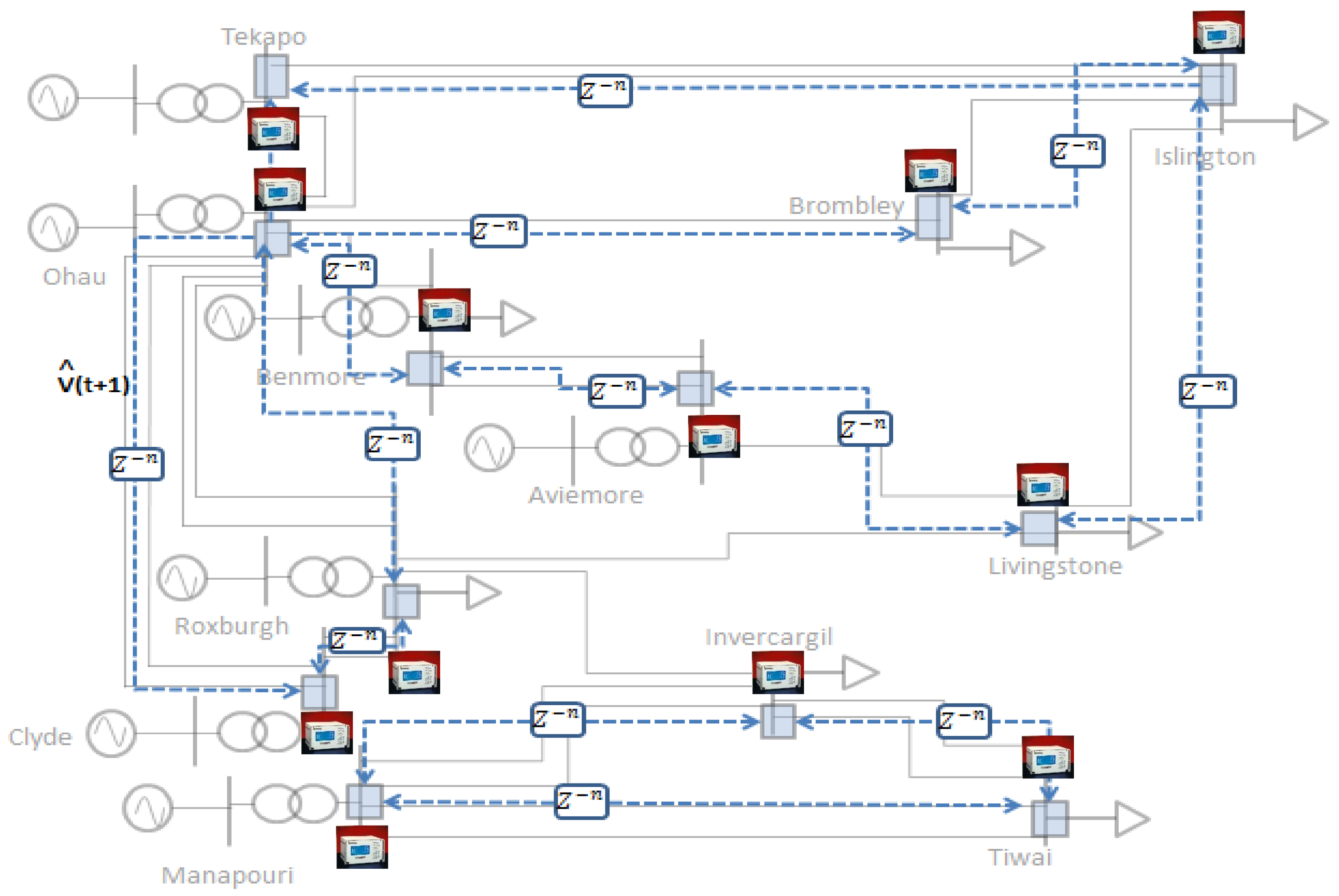
An adaptive, optimal, real-time controller based on adaptive critics design called dynamic stochastic optimal power flow (DSOPF) controller is proposed. Stochastic nature in power system can arise as a result of load and generation stochastic behaviors and due to random noise in PMU data which arises due to communication noise and measurement error.

DSOPF controller can perform real-time control action but system wide information cannot be made available to DSOPF controller in real-time because of power system communication delays which can range from a few milliseconds to several seconds depending on distance and communication media.

If state variables can be predicted ahead of time, then communication delay can be compensated for.

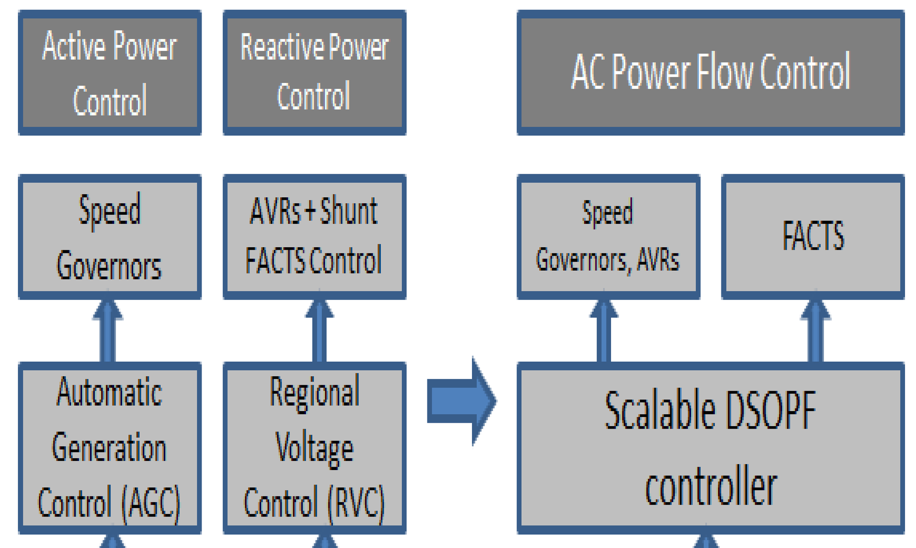
Hence, a scalable wide area monitoring system that can predict state variables ahead of time is developed. Scalability is achieved by using cellular architecture called cellular computational network (CCN). This module can effectively compensate for communication delays and hence can enable DSOPF controller to perform real-time control with system wide information.

Test System



The figure shows bus voltage prediction layer for the test system. Cells are superimposed on top of one line diagram to show how topology is captured in CCN framework . Connectivity between cells are shown as directed arrows.

Scalable Real-Time DSOPF Controller



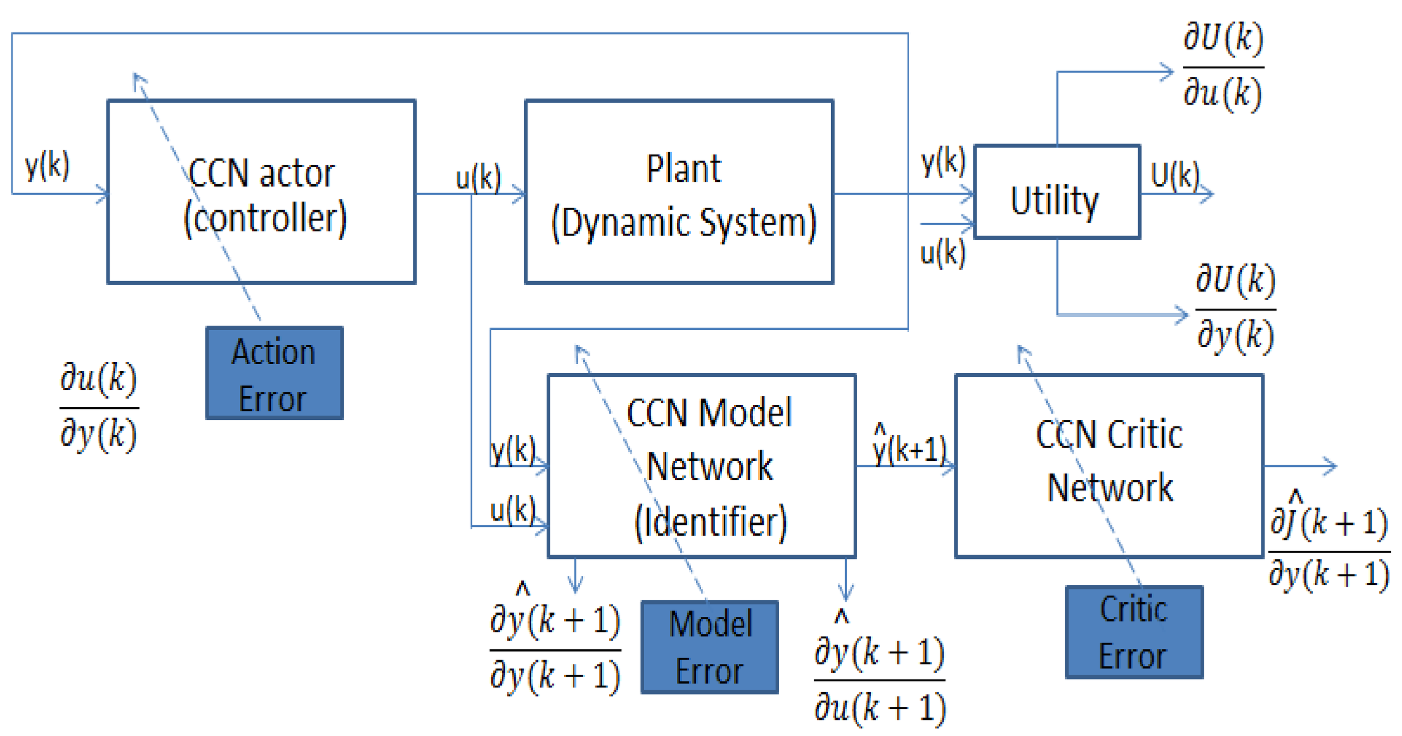
Traditional power system operation-control structure and proposed structure for a scalable DSOPF real-time control.

The model network will learn system dynamics and will predict state variables for next time step. The actor formulates the best possible control strategy, given the current state of the system and its expected course

The reference set points viewed as optimal control signals by the actor will be evaluated by critic network with derivative of cost-to-go function J.

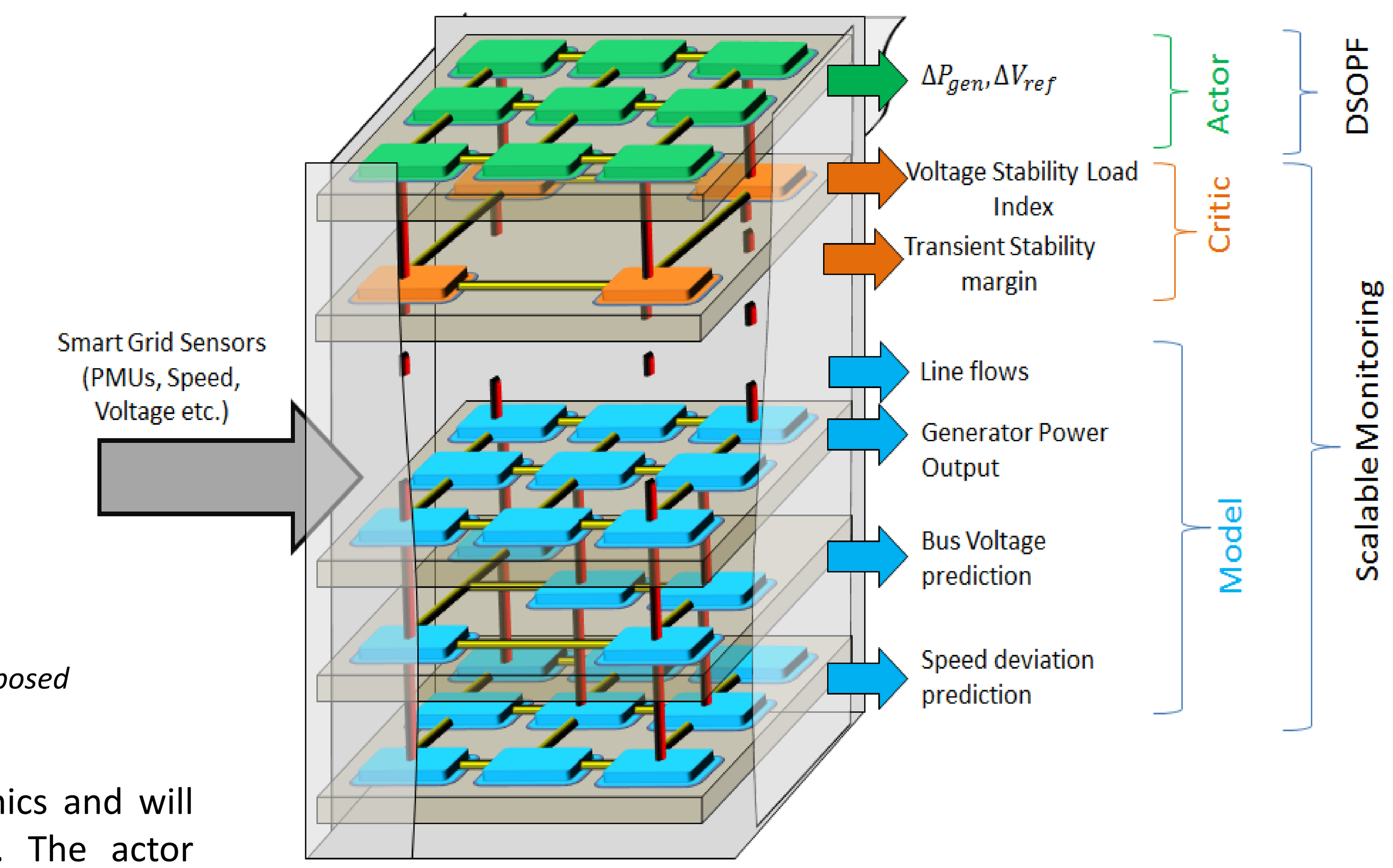
$$J(k) = \sum_{i=1}^{\infty} \gamma^{i}.U(k+i)$$

DHP Neurocontroller



Schematic diagram of DHP neurocontroller

Cellular Computational Network



Cellular Computational networks, cells in a layer are grouped together based on the state variable predicted.

In theory, if the critic weights converged to the right value, then the function J would serve as the Lyapunov function guaranteed to stabilize the overall system, if the system is controllable.

The critic and actor will work in tandem to determine control variables that would yield minimum value for derivative of cost-to-go function.

Scalability of Cellular Computational Networks

Test System	Cellular MLP	Equivalent single MLP
12-bus (4 Generator)	n=6,m=12,r=1, N=4	n=16,m=32,r=4
	No of weights= 336	**No of weights=640**
68-bus (16 Generator)	N=6,m=12,r=1,N=16	N=64,m=128,r=16
	No of weights=1344	**No of weights=10240**

n- no of input neurons, m- no of hidden layer neurons, r- no of output neurons,
N- no of cells (applicable only to cellular structure)

Utility Function

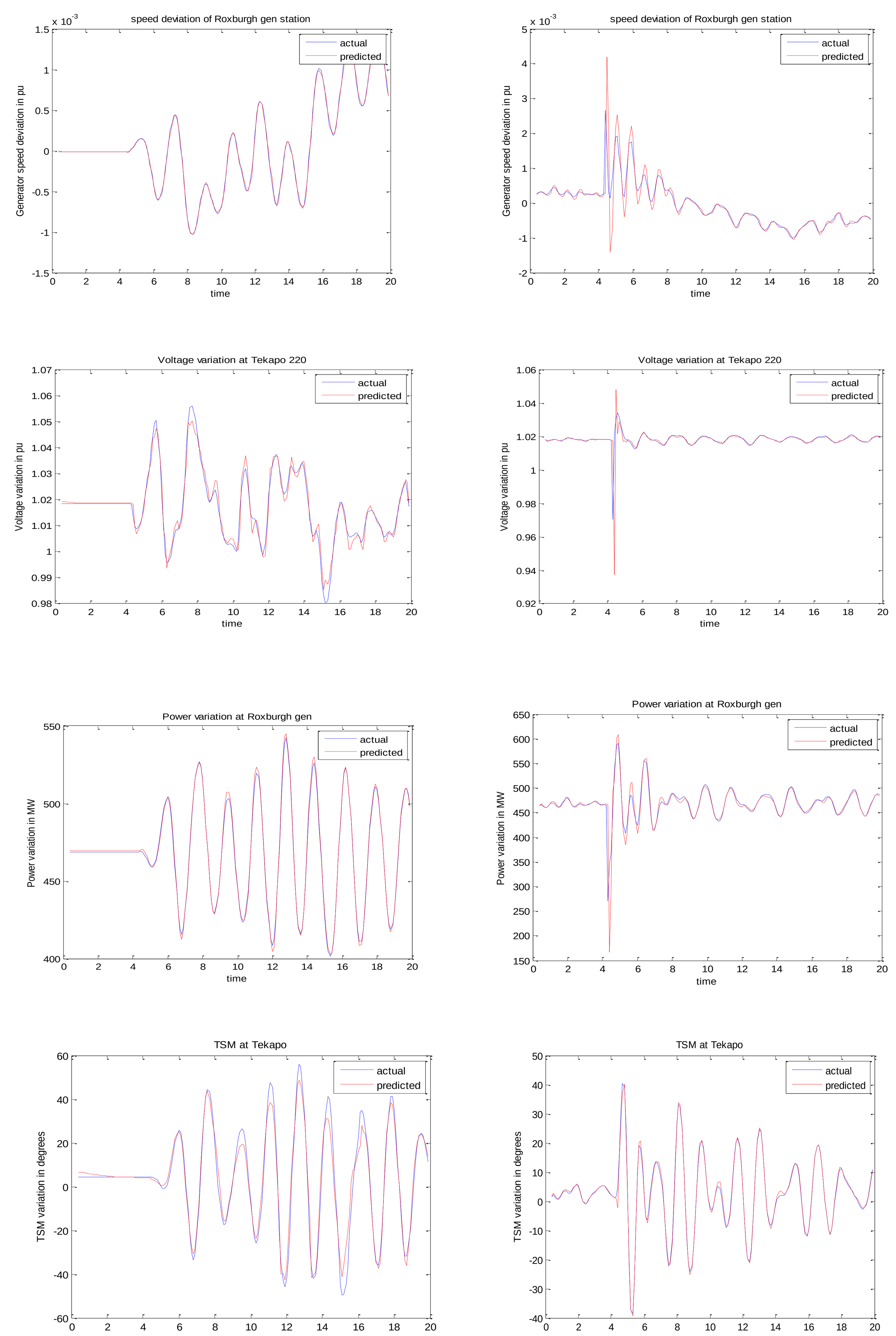
$$U = U_{fuel} + U_{loss} + U_{control} + U_{reg}$$

$$U_{fuel} = w_{fuel} \sum_{i=1}^{n_{gen}} F_{Gi} \, ; \; U_{loss} = w_{loss} \sum_{i=1}^{n\_lines} P_{loss,i}$$

$$U_{control} = w_{Pg} \sum_{i=1}^{n_{gen}} P_{Gi} + w_{Vg} \sum_{i=1}^{n_{gen}} V_{Gi}$$

$$U_{reg} = w_{V} \sum_{i=1}^{n\_bus} \Delta V_i + w_{tie} \sum_{i=1}^{n\_tie} \Delta P_i + w_{freq}\, \Delta f$$

Preliminary Results



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