
Research in Electric Power Systems

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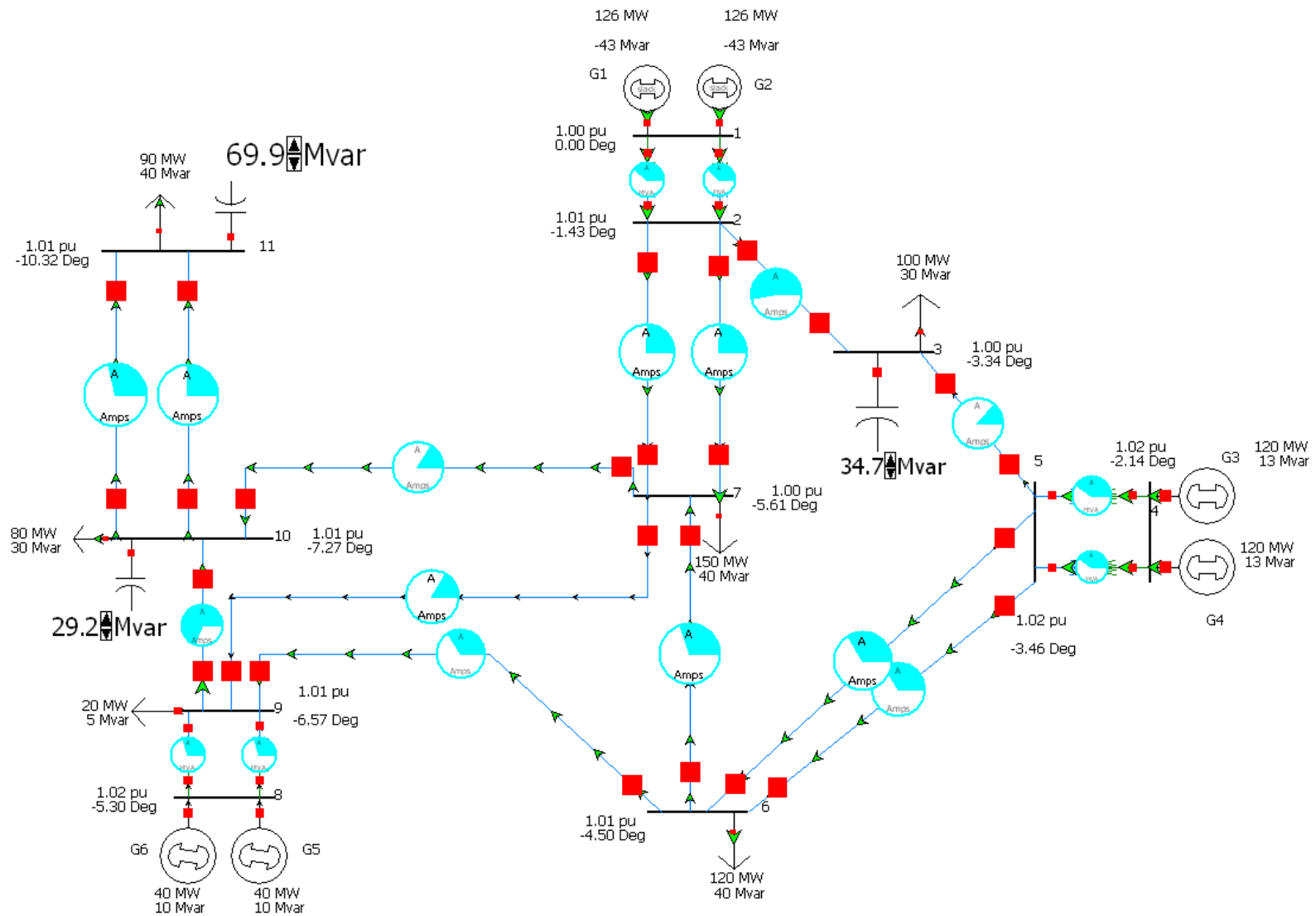
KIOS Research Center for Intelligent Systems and Networks -- University of Cyprus



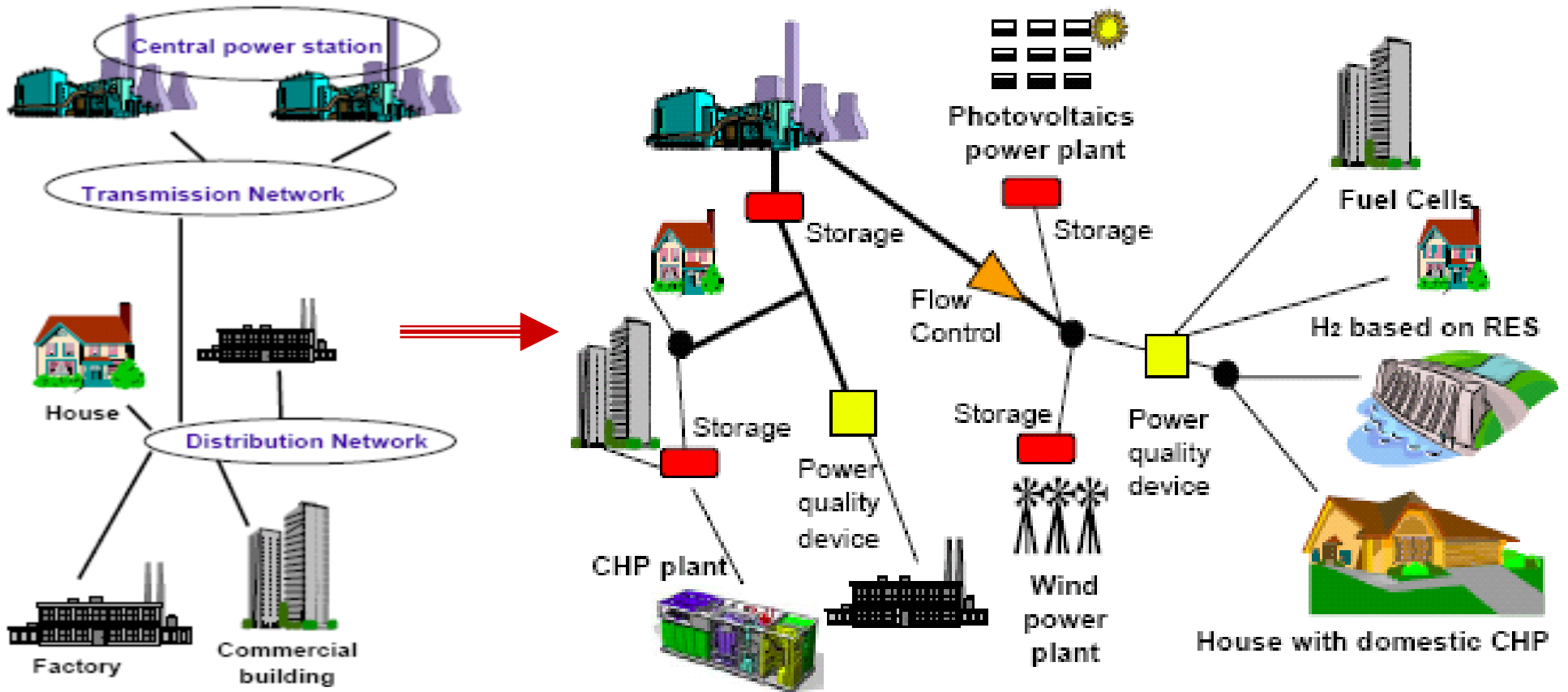
- What are power systems?
- Key challenges
- Example 1: Economic dispatch of generators
- Example 2: Synchronized measurements in power systems
- Example 3: Electric load forecasting
- Conclusions



What are power systems?



What are power systems?



Key challenges

- **System optimization/efficiency increase**
- **Smart networks**
- **Integration of renewable energy sources**
- **Reliability**
- **Security**
- **Wide area visibility/monitoring**
- **Wide area control**
- **Power systems are critical infrastructure systems**



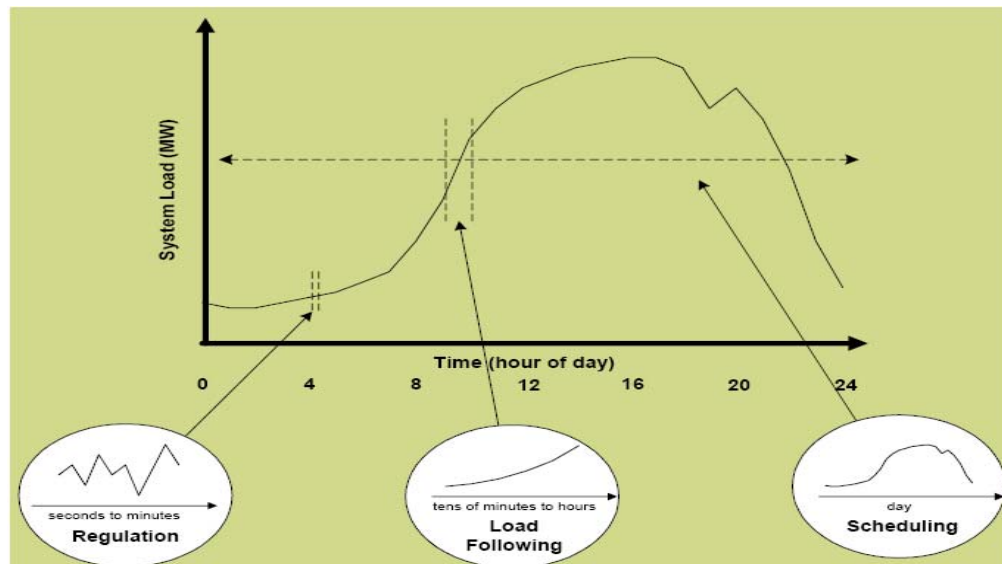
Economic dispatch

Definition:

The optimal allocation of the load demand to the committed generating units in order to minimize the generation cost (or maximize the profit) and continuously respect the system constraints.

Power system loads are cyclical. Therefore the installed generation capacity is usually much greater than the current load.

This allows options on how to meet the current load.



Economic dispatch

Generators can be separated into:

- base-load units: large coal/oil/nuclear; always ON at rated power.**
- mid-load or modulation units: smaller coal or oil units that cycle ON/OFF daily**
- peak load units: combustion turbines used only for several hours during periods of high demand**



Economic dispatch: Formulation

Objective function:

- *smooth* $\min F_t = \sum_{i=1}^n a_i + b_i P_i + c_i P_i^2$

- *non-smooth* $\min F_t = \sum_{i=1}^n a_i + b_i P_i + c_i P_i^2 + |e_i \cdot \sin(f_i (P_i^{\min} - P_i))|$

Constraints (*hard constraints*)

- balance constraint
- transmission constraints
- generation limits
- ramp rate limits
- prohibited operating zones

Constraints (*soft constraints*)

- emission constraints
- spinning reserve constraints



Economic dispatch: Solution methods

➤ Conventional methods:

- *“merit order”*
- *lambda iteration method*
- *base-point and participation factors method*
- *gradient methods*
- *dynamic programming*

➤ Computational intelligence techniques:

- *artificial neural networks (ANN)*
- *genetic algorithms (GA)*
- *evolutionary based methods (EP)*
- *simulated annealing (SA)*
- *tabu search (TS)*
- *ant colony optimization (ACO)*
- *fuzzy logic*
- *game theory*



Economic dispatch: Our proposed solution

GA-API: Combines two computational intelligence methods: Genetic algorithms and API

➤ *API*

- nice *hill climbing* behavior
- has poor use of the memory, that generally characterizes ant colony systems

➤ *GA*

- good *search space covering*
- can locate good solutions, even for difficult search spaces
- weak search around the global



Economic dispatch: Case studies

Comparison to other methods – smooth cost function with prohibited operating zones

	GA binary	GA *	PSO	PSO- LRS	Modified GARC	GA-API
P_1 (MW)	456.46	474.81	447.50	447.44	447.49	447.12
P_2 (MW)	168.26	178.64	173.32	173.34	173.32	173.41
P_3 (MW)	258.68	262.21	263.47	263.36	263.46	264.11
P_4 (MW)	132.66	134.28	139.06	139.13	139.07	138.31
P_5 (MW)	170.97	151.90	165.48	165.51	165.47	166.02
P_6 (MW)	89.10	74.18	87.13	87.17	87.13	87.00
Losses (MW)	13.13	13.02	12.96	12.96	12.96	12.98
Generation output (MW)	1276.13	1276.03	1276.01	1275.95	1275.96	1275.97
Cost of generation (\$/h)	15451.66	15459.00	15450.00	15450.0	15449.77	15449.78

Economic dispatch: Case studies

Comparison to other methods – non-smooth cost function without prohibited operating zones

	GA binary	Modified GARC	GA-API
P_1 (MW)	408.24	495.09	499.98
P_2 (MW)	194.09	150.45	199.89
P_3 (MW)	263.42	223.11	225.75
P_4 (MW)	138.93	149.40	124.95
P_5 (MW)	155.39	147.94	150.19
P_6 (MW)	115.72	109.72	74.97
Losses (MW)	12.89	12.07	13.13
Generation output (MW)	1275.83	1275.70	1276.13
Cost of generation (\$/h)	15938.08	15634.70	15607.47

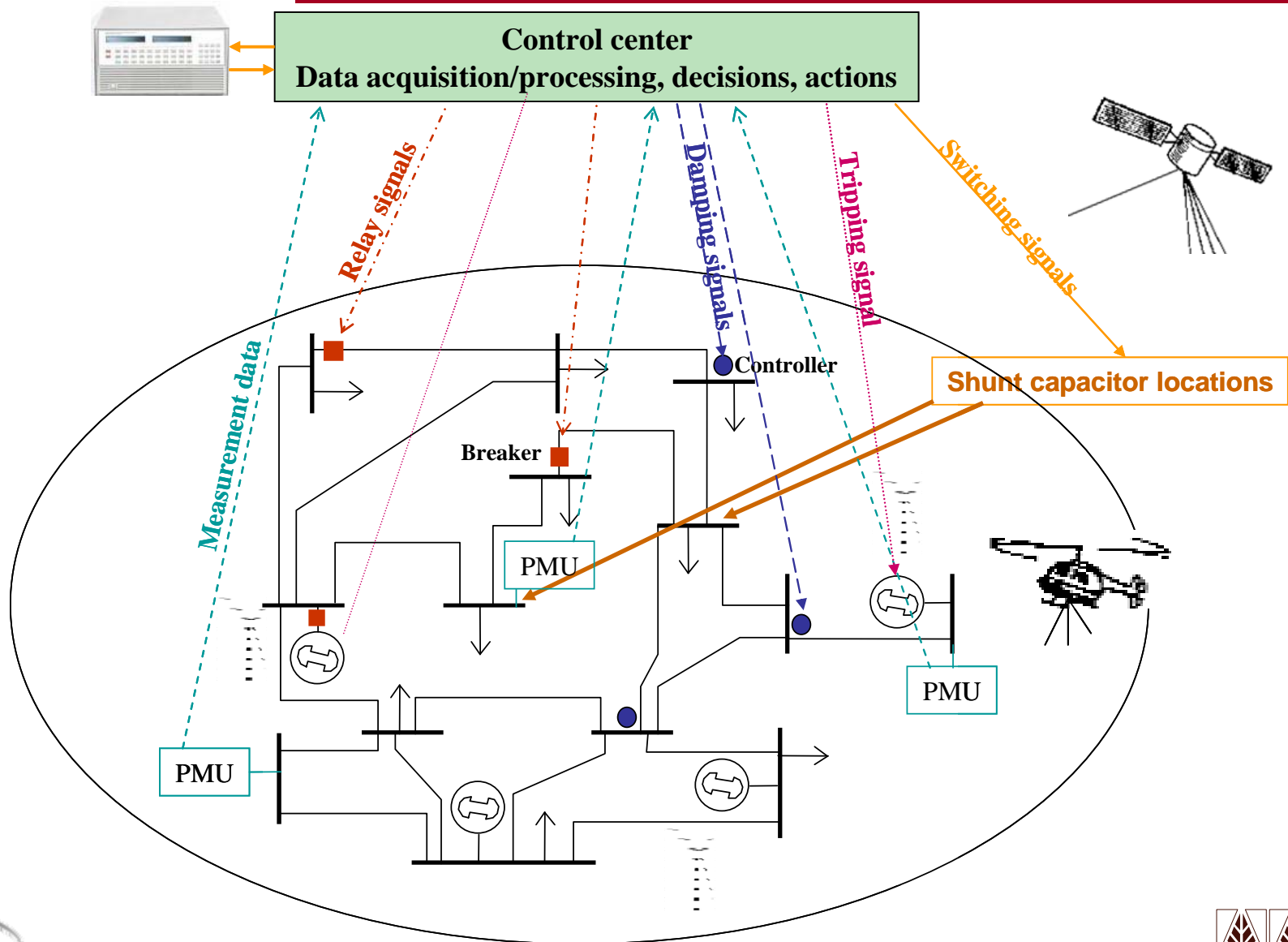


Synchronized measurements in power systems

- **Control and monitoring of power systems relies heavily on measurements disbursed throughout the system**
- **Perform fundamental research on the subject of massively deployed sensors for societal infrastructure systems and mainly the electric power system grid**
- **Examine operational and physical security, state estimation, improvement in the system response, and alarm prioritization.**



Synchronized measurements: The vision



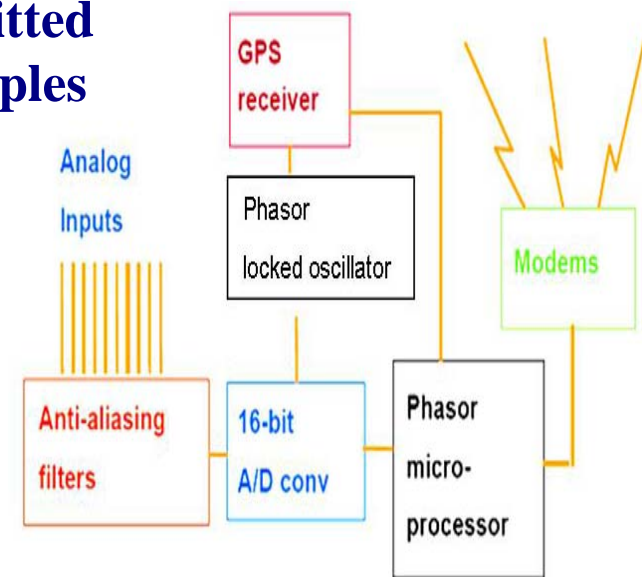
Synchronized measurements: Phasor measurement units (PMUs)

Measure 50/60Hz AC waveforms (voltages and currents) typically at a rate of 48 samples per cycle (2880 samples per second).

A phase-lock oscillator along with a Global Positioning System (GPS) reference source provides the high-speed synchronized sampling with 1 microsecond accuracy.

The resultant time-tagged phasors can be transmitted to a local or remote receiver at rates up to 60 samples per second.

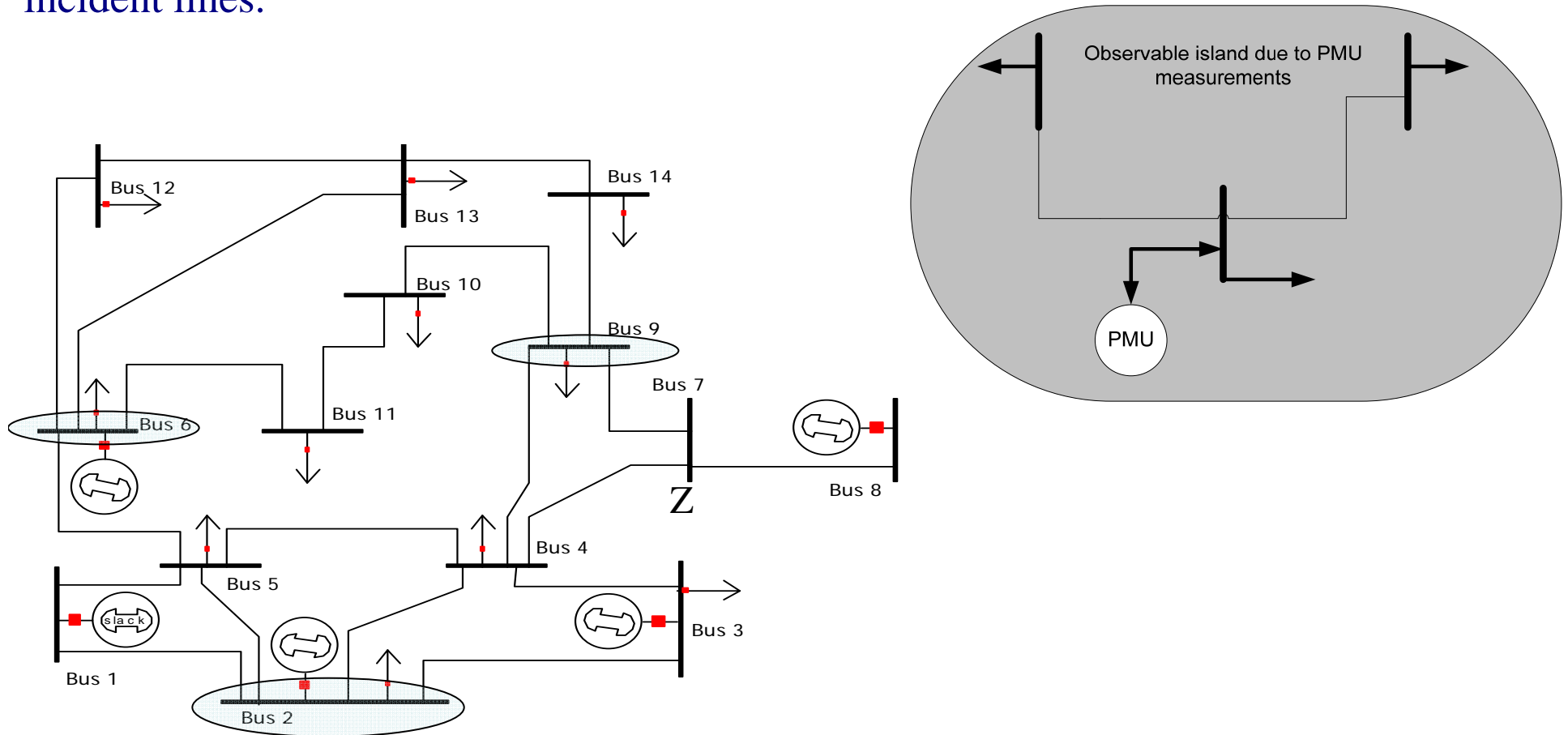
- ❖ Time synchronized data
- ❖ Observe dynamic behavior
- ❖ Wide area visibility and monitoring
- ❖ Direct measurement of phase angles
- ❖ Disadvantage: Very expensive



**Phasor Measurement Unit
Block Diagram**

Synchronized measurements: PMU placement

When a PMU is placed at a bus, it can measure the phase angle of the voltage at that bus, as well as the phase angles of the voltages at the busses at the other end of all the incident lines.



Synchronized measurements: PMU placement

- **Place PMUs at strategic locations in the power system**
- **Multiple objectives (depending on the desired performance characteristics):**
 - **Full observability (placement of minimum number of PMUs)**
 - **State estimator enhancement (combine with conventional measurements)**
 - **Minimize measurement uncertainty**
 - **Ensure full observability for single PMU or single line outage**
 - **Achieve wide area visibility (real time)**
 - **Transition from wide area measurement systems to wide area control systems**



Synchronized measurements: Problem formulation

The elements of the binary connectivity matrix H for a power system, used in the formulation of the optimization problem, are defined as,

$$h_{ij} = \begin{cases} 1 & \text{if } i = j \\ 1 & \text{if bus } i \text{ and } j \text{ are connected} \\ 0 & \text{otherwise} \end{cases}$$

The binary vector $\mathbf{x} \in R^n$ is defined as,

$$x_i = \begin{cases} 1 & \text{if a PMU is placed at bus } i \\ 0 & \text{otherwise} \end{cases}$$

➡ The entries of the product $H\mathbf{x}$ therefore represent the number of times a bus is observed by the PMU placement set defined by \mathbf{x} .



Synchronized measurements: Problem formulation

The objective function $V(\mathbf{x})$ for optimization is formulated as in an integer quadratic programming problem,

$$V(\mathbf{x}) = \lambda(\mathbf{N} - \mathbf{H}\mathbf{x})^T \mathbf{R}(\mathbf{N} - \mathbf{H}\mathbf{x}) + \mathbf{x}^T \mathbf{Q}\mathbf{x}$$

where $\lambda \in R$ is a weight, and $\mathbf{N} \in R^n$ is a vector representing the upper limits of the number of times each bus can be observed, the diagonal matrix $\mathbf{R} \in R^{n \times n}$ has entries r_{ii} representing the ‘significance’ of each bus i , the diagonal matrix $\mathbf{Q} \in R^{n \times n}$ has entries q_{ii} allowing for the representation of varying installation costs of the PMUs at different busses.

☞ In the generic case, where all busses are equally significant and the PMU installation cost at all busses is the same, \mathbf{Q} and \mathbf{R} are equal to the identity matrix.



Synchronized measurements: Example

Connectivity matrix:

$$A = \begin{bmatrix} 1 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 1 & 1 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 1 & 1 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 1 & 1 \end{bmatrix}$$

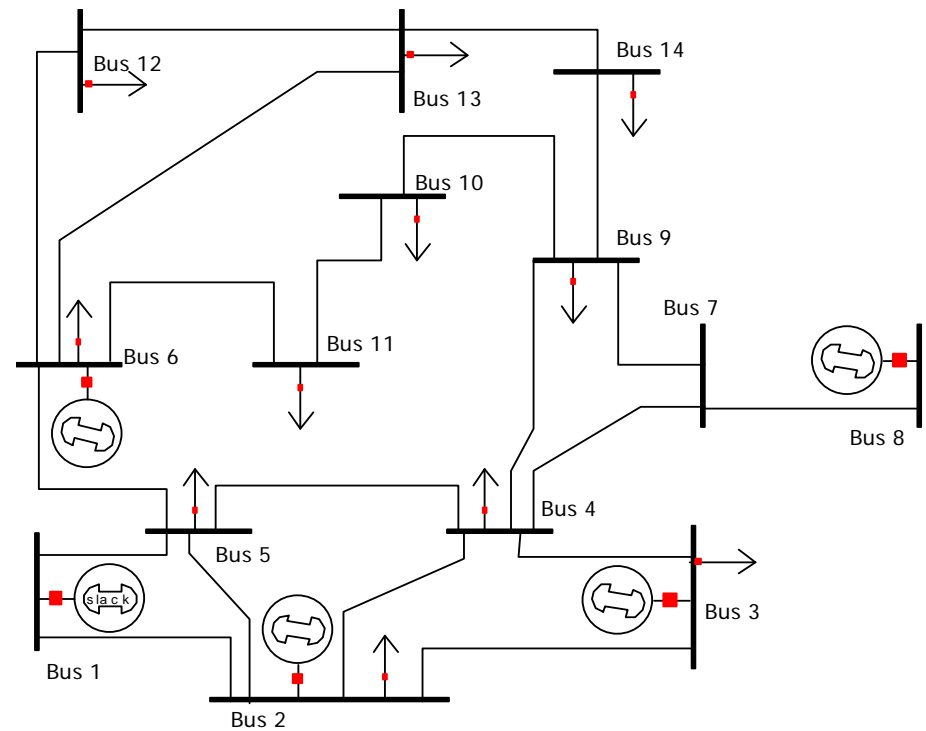
Line outage example:

If the transmission line between the busses 2 and 3 is removed from service, $A(3,2)$ and $A(2,3)$ will be zero.

The additional set of constraints is,

$$\begin{bmatrix} 1 & 1 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \mathbf{x} \geq \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

IEEE 14-bus test system



Optimal locations of PMUs for the IEEE 14-bus test system

System configuration	Optimal PMU locations
Normal operating conditions	2, 6, 7, 9
Considering single branch or PMU outages	2, 4, 5, 6, 7, 8, 9, 11, 13



Electric load forecasting

- Short term load forecasting with a 24 hour horizon
- Use of neural networks to develop a system that can perform load forecasting given historical load data and meteorological parameters
- Determine the chronological, seasonal, and meteorological factors that affect load demand in Cyprus
- Wide range testing of the proposed system using actual historical data
- Design a user friendly software that can perform short term load forecasting



Electric load forecasting: Background info

- The electric load demand is affected by chronological and meteorological factors
- The load demand curves for weekdays are different than load demand curves for weekends
- The load demand curve for the winter is different than the summer one
- Meteorological factors such as temperature, humidity, speed and direction of wind, rainfall, and cloudness affect the energy consumption
- Different load profile for different geographical areas
- In some areas some of the meteorological factors affect the load demand, and in others they don't.



Electric load forecasting

General comments:

- Almost all methods are suited to the special characteristics of individual electric utilities and to the geographical and meteorological characteristics of each area
- The most important element for any short term load forecast is the historical load demand data and the weather conditions
- The methods that are based on non linear models and especially those that use computational intelligence techniques are the most suitable to determine the relationship between meteorological factors, historical data, and future electricity demand.

Our work concentrated on three different structures of neural networks:

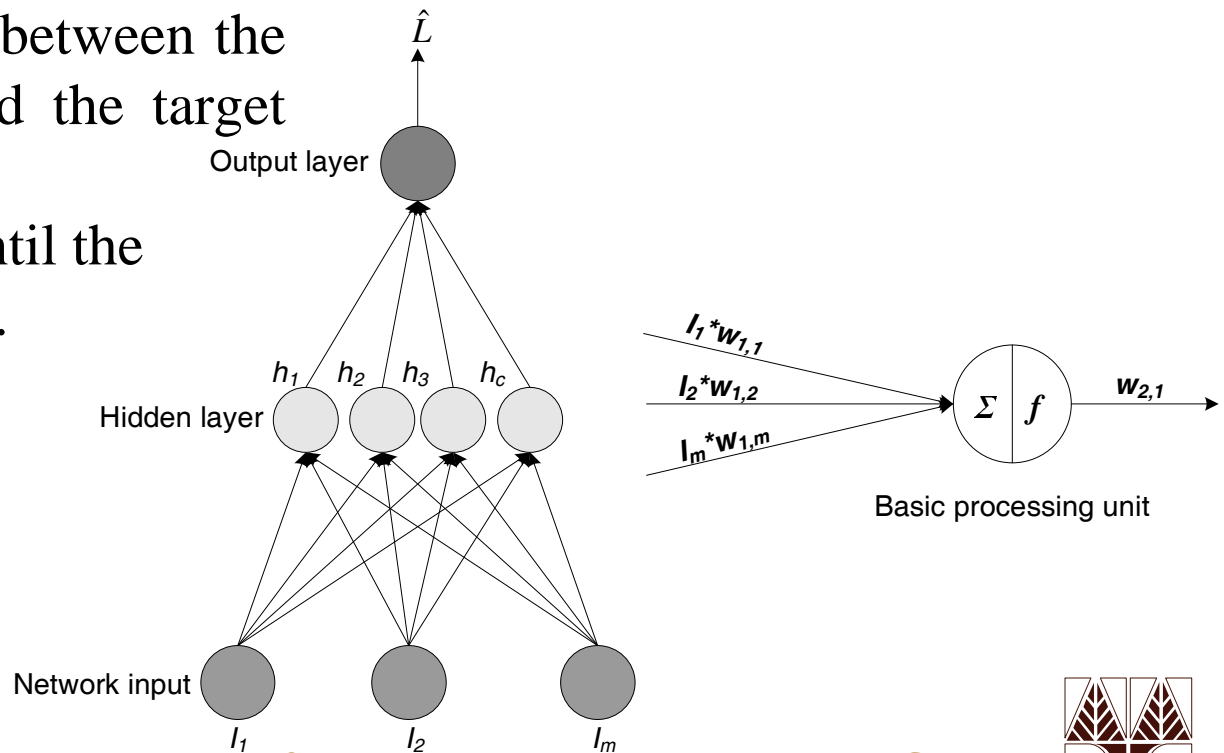
- Sigmoidal networks (MLP)
- Radial basis functions (RBF)
- Elman networks



Electric load forecasting: Example of a network used

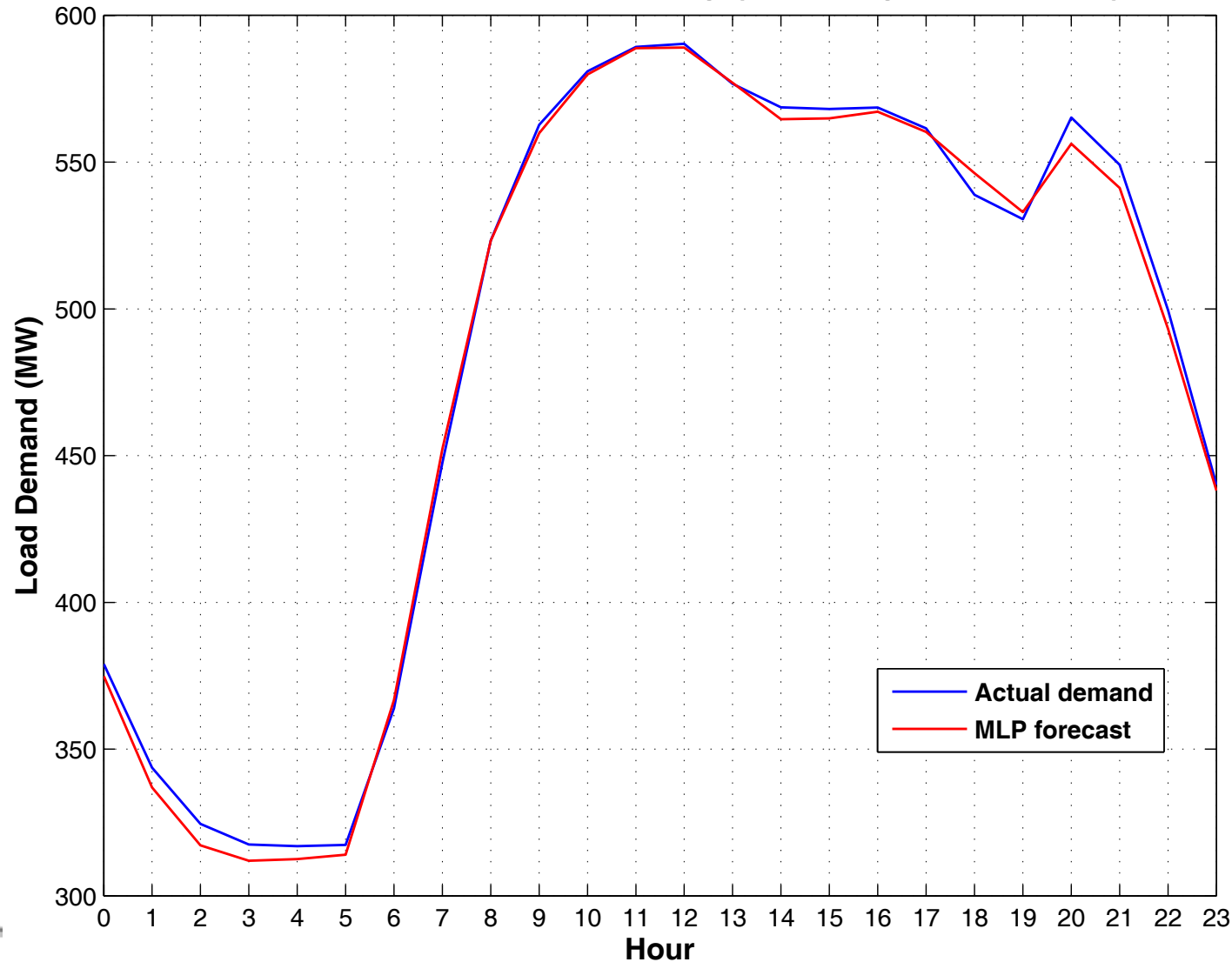
Sigmoidal networks (MLP)

- The input data are independent multidimensional points (historical load data and meteorological parameters)
- The network is trained through the error-backpropagation algorithm, which determines the derivatives of an error function with respect to the weights of the network, and attempts to minimize the square error between the network output values and the target values for these outputs
- The weights are updated until the minimum error is achieved.



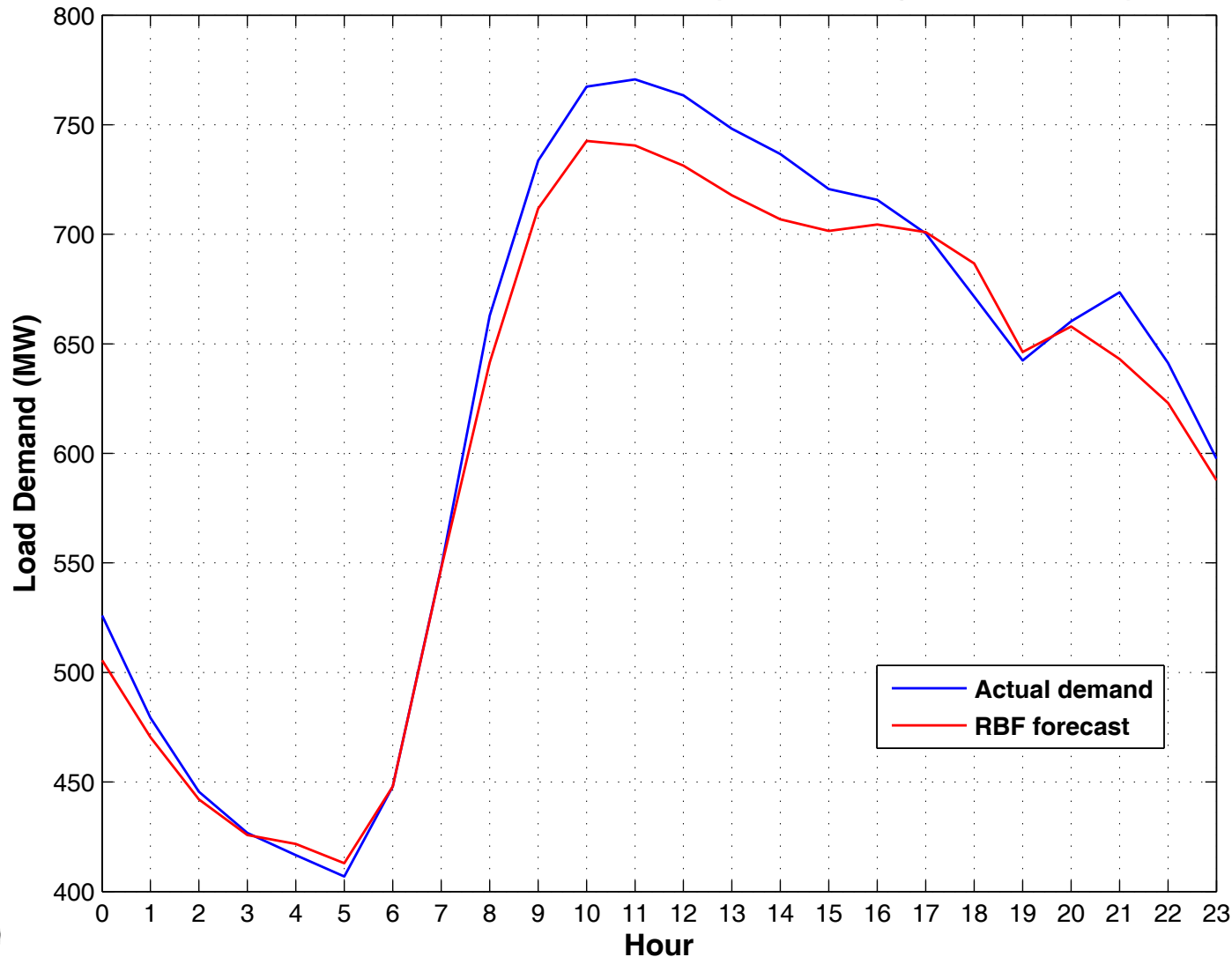
Electric load forecasting: Representative forecasts

Best forecast with MLP for May (Thursday, MAPE: 0.86)



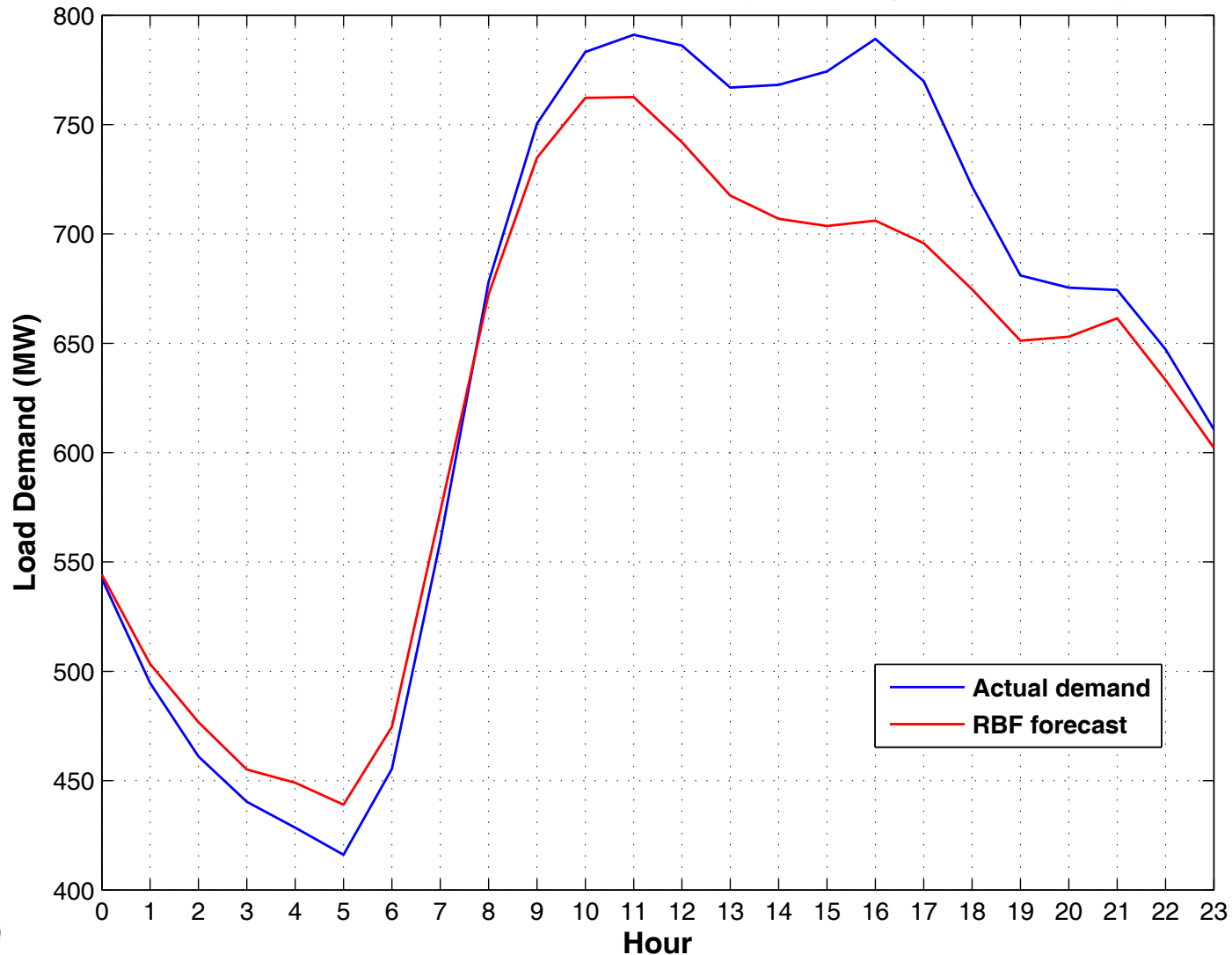
Electric load forecasting: Representative forecasts

Best forecast with RBF for Jun (Wednesday, MAPE: 2.16)



Electric load forecasting: Representative forecasts

Worst forecast with RBF for Jun (Thursday, MAPE: 4.33)



Further reading

Synchronized measurements

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2. J. W. Stahlhut, G. T. Heydt, and E. Kyriakides, "A comparison of local vs. sensory, input-driven, wide area reactive power control," IEEE Power Engineering Society General Meeting, Super Session "Vision 2020", Tampa, FL, USA, pp. 1-7, June 2007.
3. S. Chakrabarti, D. Eliades, E. Kyriakides, and M. Albu, "Measurement uncertainty considerations in optimal sensor deployment for state estimation," IEEE International Symposium on Intelligent Signal Processing (WISP 2007), Madrid, Spain, pp. 1-6, Oct. 2007.
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5. S. Chakrabarti and E. Kyriakides, "Placement of phasor measurement units for state estimation with voltage stability considerations," Australasian Universities Power Engineering Conference, Australia, pp. 38-42, Dec. 2007.
6. S. Chakrabarti and E. Kyriakides, "Optimal placement of phasor measurement units for power system observability," IEEE Transactions on Power Systems, vol. 23, no. 3, pp. 1433-1440, Aug. 2008.
7. S. Chakrabarti, E. Kyriakides, and M. Albu, "Uncertainty in power system state variables obtained through synchronized measurements," IEEE Trans. on Instrumentation and Measurement, pp. 1-6, (accepted July 08).
8. S. Chakrabarti, E. Kyriakides, and D. G. Eliades, "Placement of synchronized measurements for power system observability," IEEE Transactions on Power Delivery, pp. 1-8, (accepted Sep. 08).



Further reading

Economic dispatch

1. I. Ciornei and E. Kyriakides, “A multi-agent genetic algorithm for the solution of the economic dispatch problem,” *3rd International Conference on Energy and Environment (CIEM 2007)*, Bucharest, Romania, pp. 115-123, Nov. 2007.
2. I. Ciornei and E. Kyriakides, “Generation dispatch of the future hybrid renewable power system in a deregulated energy market environment,” *International Workshop on Deregulated Electricity Market Issues in South-Eastern Europe (DEMSEE08)*, Nicosia, Cyprus, pp. 1-8, Sep. 2008.

Electric load forecasting

1. E. Kyriakides and M. Polycarpou, “Short term electric load forecasting: a tutorial,” chapter 16 in *Trends in Neural Computation*, Berlin: Springer-Verlag, pp. 391-418, Eds. K. Chen, W. Lipo, 2007.
2. M. Markou, E. Kyriakides, and M. Polycarpou, “24-hour ahead short term load forecasting using multiple MLP,” *International Workshop on Deregulated Electricity Market Issues in South-Eastern Europe (DEMSEE08)*, Nicosia, Cyprus, pp. 1-6, Sep. 2008.

