

# Agent-Based Test Beds for Power Industry Research, Teaching, and Training

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# Presentation Outline

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- \* Why Agent-Based Test Beds for Power Industry Research, Teaching, and Training?

- \* Adventures in Test-Bed Development for Restructured Wholesale Power Markets:

**AMES** = **A**gent-based **M**odeling of **E**lectricity **S**ystems

- \* Illustrative Dynamic 5-Node Test Case Results

# The Complexity of Power Systems

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- Many industrialized economies are in the process of restructuring the way power is produced & distributed
- These restructured power systems are immensely complicated, encompassing
  - ◆ Physical constraints
  - ◆ Institutional arrangements
  - ◆ Behavioral dispositions of human participants
- To be useful and informative, power system studies need to take proper account of all three elements.

# Why Agent-Based Modeling (ABM) Tools for Power Systems?

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- ABM tools are designed to handle complex systems.
- ABM tools permits researchers to construct test beds in the form of **computational virtual worlds**
- Starting from user-specified initial conditions, world events are driven entirely by **agent interactions**.
- **Agents** can range from entities with no cognitive function (e.g., transmission grids) to sophisticated decision makers capable of communication and learning (e.g., electricity traders).

# ABM and the Design of Restructured Wholesale Power Markets

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**Key Issue:** Does a proposed or actual market design ensure *efficient, orderly, & fair outcomes over time*?

## **ABM Approach:**

- ◆ Construct an *agent-based test bed* that models a wholesale power market operating under the design
- ◆ *Let profit-seeking traders have learning capabilities*, and let the wholesale power market evolve over time.
- ◆ *Observe and evaluate* the resulting outcomes.

# Concrete Example:

## The AMES Market Test Bed

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Electric Power Research Center (a power industry consortium)

**AMES Market Package Homepage (Code/Manuals/Pubs):**  
[www.econ.iastate.edu/tesfatsi/AMESMarketHome.htm](http://www.econ.iastate.edu/tesfatsi/AMESMarketHome.htm)

# Project Context

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- ❑ In an April 2003 White Paper, the U.S. Federal Energy Regulatory Commission (FERC) proposed a market design for U.S. wholesale power markets.
- ❑ About 50% of U.S. electric power generating capacity now operates under a variant of the FERC market design.

**Our Basic Project Goal:** Systematically explore dynamic performance under the FERC market design, using Midwest (MISO) and New England (ISO-NE) as main case studies.

# Core Features of FERC's Market Design

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- Market operated by an Independent System Operator (ISO) or Regional Transmission Organization (RTO)
- Day-ahead & real-time markets for power
- Congestion managed via **Locational Marginal Pricing (LMP)**, the determination of a separate price at each grid location where power is injected or withdrawn
- ISO/RTO oversight & market power mitigation

<http://www.ferc.gov/industries/electric/indus-act/rto/rto-map.asp>



# Why Resistance to FERC's Market Design?

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- **Regions Already Operating Under the Design**

*Key cited problems:*

Lack of sufficient performance testing;

Price volatility (across the transmission grid & over time).

- **Stakeholders in Southeast and Northwest**

*Key cited problems:*

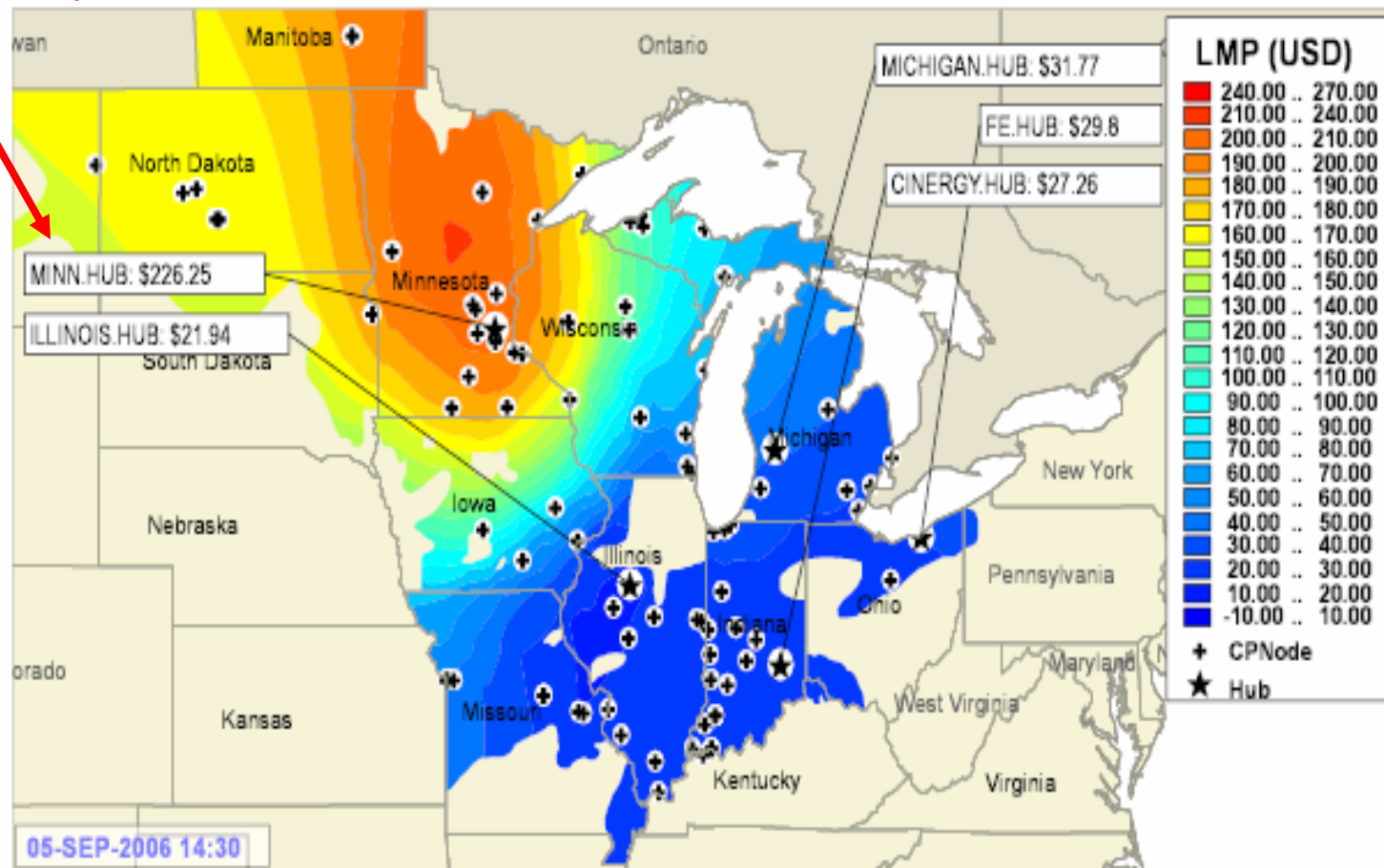
Lack of sufficient performance testing;

Questions about suitability given special local conditions (TVA, hydroelectric power...).

# Actual Electricity Prices in Midwest ISO (MISO)

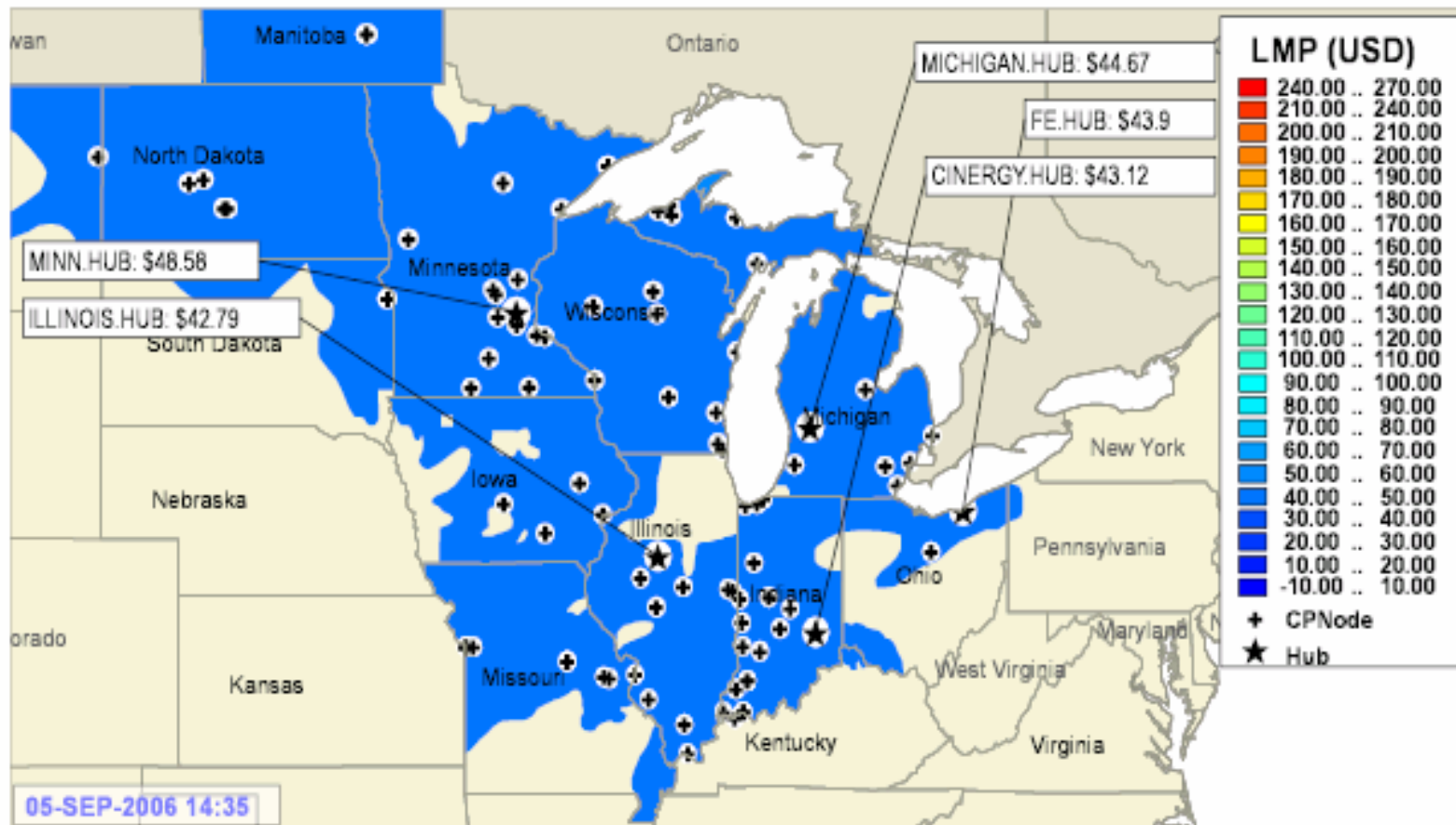
## September 5, 2006, 14:30

Note this price, \$226.25



# Five Minutes Later...

79% drop in price in 5 minutes!



# A Computational Modeling Approach

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- ❑ **Problem:** FERC's market design is a complicated mix of features
  - ➔ Difficult to model and study using standard analytical and statistical tools
- ❑ **Our Approach:** Develop an agent-based test bed permitting systematic experimental testing of
  - the FERC market design
  - new/modified market design features

# The AMES Market Test Bed

## Target Features and Release History

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- **Research/teaching/training grade test-bed**  
(2-500 pricing nodes)
- **Operational validity** ( "simple but not too simple" )
- Permits **dynamic** testing with **learning traders**
- Permits **intensive experimentation** with alternative scenarios
- **Free open-source Java implementation** (full access to code)
- **Flexible & modular** (easy to modify test bed features)
- **V1.31 released** (IEEE Power Eng. Soc. Gen. Meeting, 2007)
- **V2.0 in final testing stages**

# AMES Market Test Bed

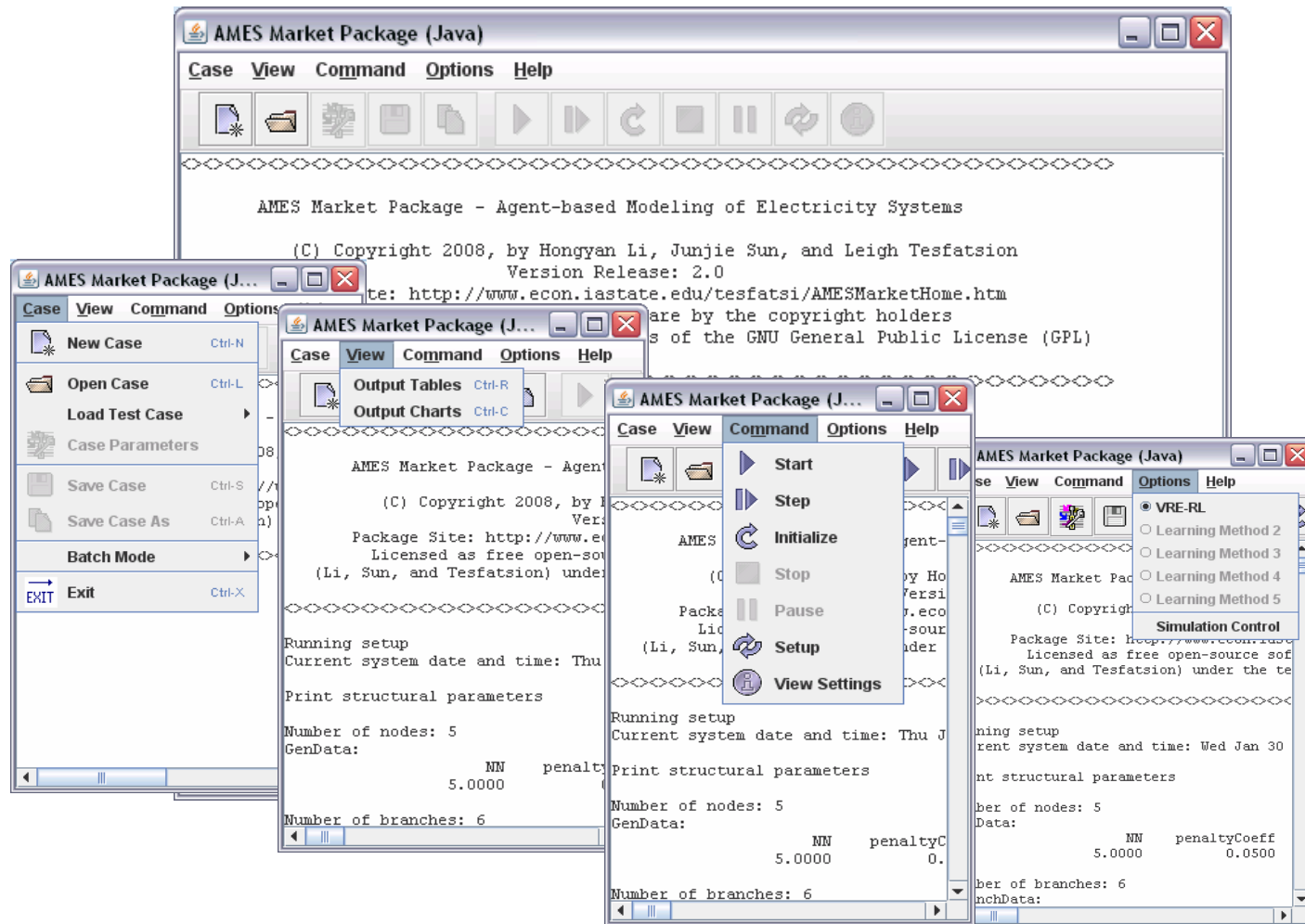
## Flexible and Modular Architecture

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- ◆ **Market protocols & AC transmission grid structure**
  - **Graphical user interface** and **modularized class structure** permit easy experimentation with alternative parameter settings and alternative institutional/grid constraints
- ◆ **Learning representations for traders**
  - **Java Reinforcement Learning Module (JReLM)**
  - “Tool box” permitting experimentation with a wide variety of learning methods (Roth-Erev, Temp Diff/Q-learning,...)
- ◆ **Optimal power flow formulation**
  - **Java DC Optimal Power Flow Module (DCOPFJ)**
  - Permits experimentation with various DC OPF formulations
- ◆ **Output displays and dynamic test cases**
  - Customizable chart/table displays & 5-node/30-node test cases

# AMES Market Test Bed Graphical User Interface (GUI)

## Tool Bar and Menus for Data Input and Output Displays



# AMES Architecture: Current Implementation

(based on business practices manuals for MISO/ISO-NE)

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## ➤ Traders

- Generators (sellers)
- Load-Serving Entities (buyers)
- **Learning abilities**

## ➤ Independent System Operator (ISO)

- System reliability assessments
- **Day-ahead bid/offer-based unit commitment**
- Real-time dispatch

## ➤ Two-settlement process

- Day-ahead market (double auction, financial contracts)
- Real-time market (settlement of differences)

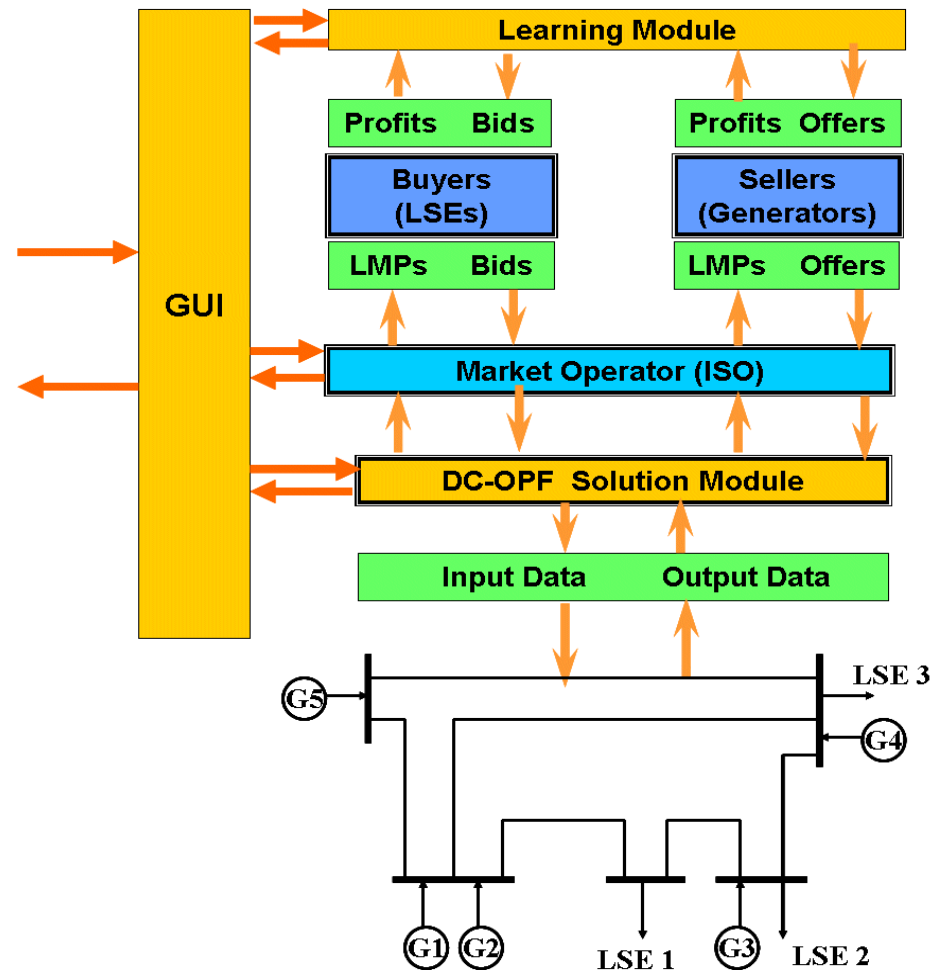
## ➤ AC transmission grid

- Generators & Load-Serving Entities (LSEs) located at various transmission nodes
- Congestion managed via Locational Marginal Pricing (LMP) determined by ISO via **DC optimal power flow (OPF)**

## Activities of AMES ISO During Each Operating Day D: Timing Adopted from Midwest ISO (MISO)

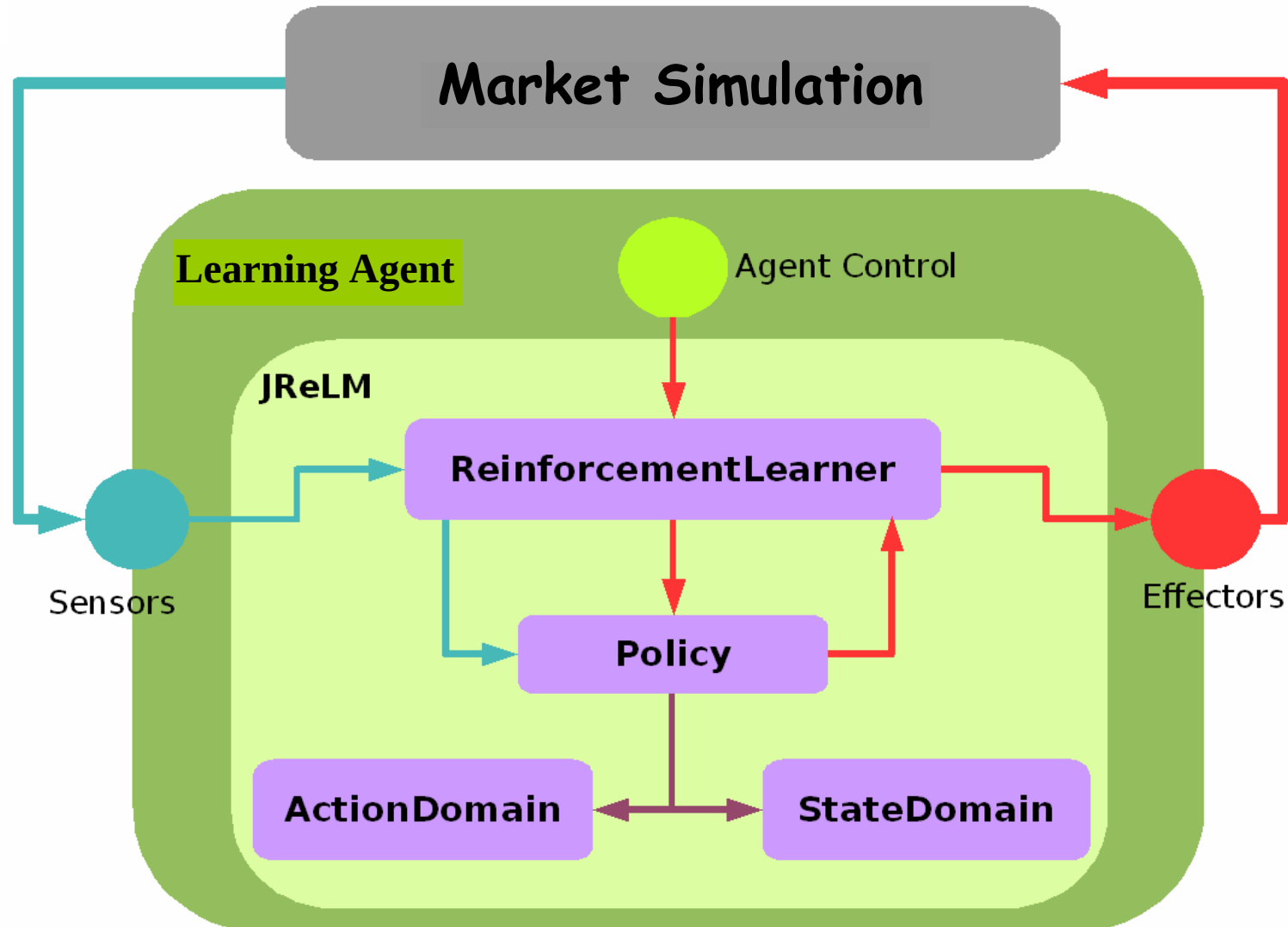
|                                                          |       |                                                                                                      |
|----------------------------------------------------------|-------|------------------------------------------------------------------------------------------------------|
| <b>Real-Time<br/>(Spot)<br/>Market<br/>for<br/>day D</b> | 00:00 | <b>Day-Ahead Market<br/>for day D+1<br/>(ISO collect bids/offers<br/>from LSEs &amp; Generators)</b> |
|                                                          | 11:00 | <b>ISO evaluates demand<br/>bids and supply offers</b>                                               |
|                                                          | 17:00 | <b>Re-Bid Period for day D+1<br/>(not yet implemented)</b>                                           |
|                                                          | 18:00 | <b>ISO solves D+1 DC OPF<br/>and posts D+1 commitment<br/>and price schedule</b>                     |
| <b>Real-Time<br/>Settlement</b>                          | 23:00 | <b>Day-Ahead Settlement</b>                                                                          |

# AMES Dynamics for No-Shock Case (day-ahead contracts fulfilled as planned)



# AMES Java Reinforcement Learning Module - JReLM

(Charles J. Gieseler, Comp Sci M.S. Thesis, 2005)



# AMES Generator (Learning Agent)

## Public Access:

### // **Public Methods**

getMarketProtocols(supply offer reporting, settlement,...);  
getMarketProtocols(ISO market power mitigation);  
Methods for receiving data;  
Methods for retrieving Generator data.

## Private Access:

### // **Private Methods**

Methods for gathering, storing, and sending data;  
Methods for calculating expected & actual profit outcomes;  
Method for updating my supply offers (**LEARNING via JReLM**)

### // **Private Data**

My capacity, grid location, cost function, current wealth... ;  
Data recorded about external world (LMPs, cleared offers,...);  
Address book (communication links).

# What do AMES Generators Learn?

## Hourly Supply Offers for the Day-Ahead Market

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- Supply offer for each generator  $i$  = *reported* linear marginal cost function over a *reported* operating capacity interval for real power  $p_{Gi}$  (in MWs):

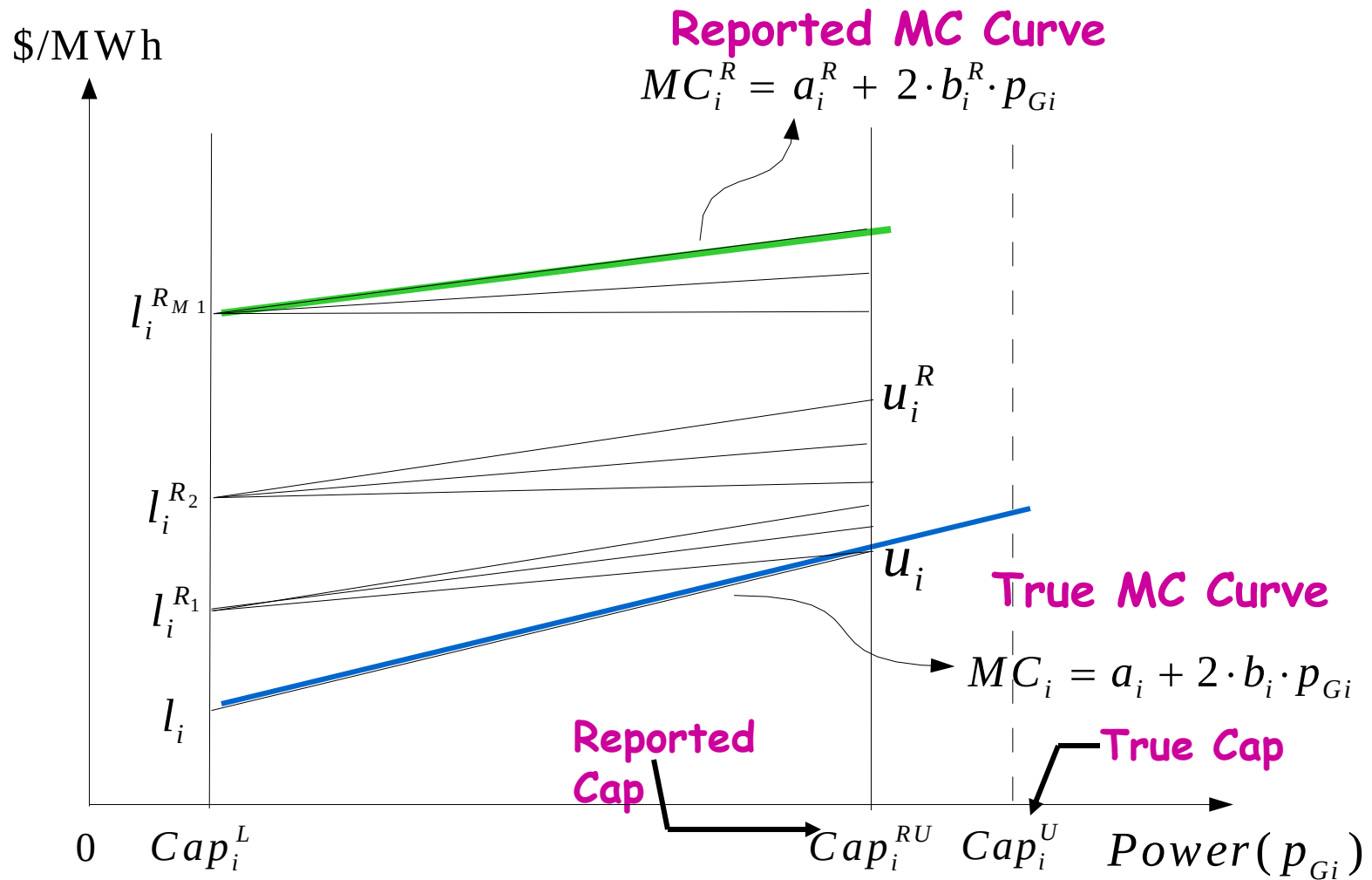
$$MC^R_i(p_{Gi}) = a^R_i + 2b^R_i p_{Gi}$$

$$Cap_i^L \leq p_{Gi} \leq Cap_i^{RU}$$

Generators can strategically report higher-than-true marginal costs and/or withhold capacity.

# Generator i's Action Domain

(Collection of possible reported marginal cost functions  $MC_i^R$  over possible reported operating capacity intervals)



# How Might AMES Generators Learn?

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\* One possibility:

*Reactive Reinforcement Learning (RL)*

Asks....

Given *past* events, what action  
should I take *now* ?

**Examples:** Three-parameter RL based on human-subject experiments (Roth-Erev, 1995,1998), Variant Roth-Erev RL for electricity double auctions (Nicolaisen, Petrov, Tesfatsion, IEEE TEC, 2001)

# How Might AMES Generators Learn...

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\* Another possibility:

*Anticipatory Learning*

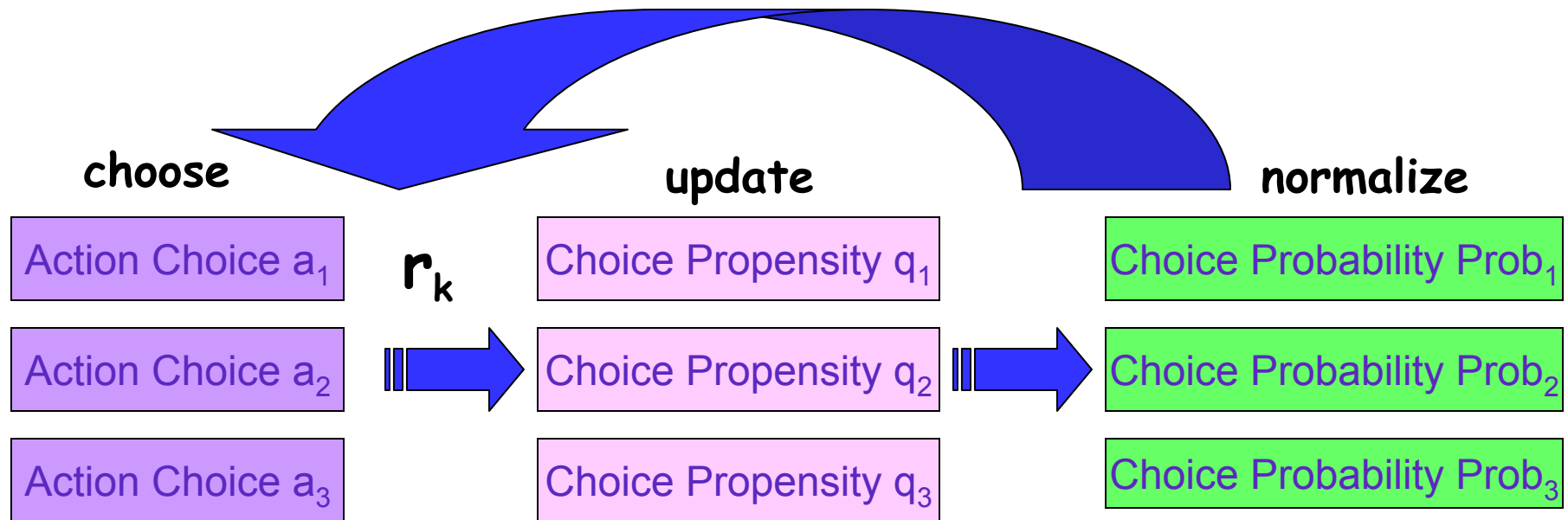
Asks....

If I take this action *now*, what will  
happen in the *future*?

**Examples:** Q-Learning (Watkins, 1989); Temporal-Difference  
Reinforcement Learning (Sutton/Barto, 1998)

# Example: Reactive Reinforcement Learning

VRE = Variant Roth-Erev (Nicolaisen et al., 2001)



- Each Generator maintains action choice propensities  $q$ , normalized to action choice probabilities Prob, to choose actions. A good (bad) profit  $r_k$  for action  $a_k$  results in a strengthening (weakening) of the propensity  $q_k$  for  $a_k$ .

# VRE Updating of Action Propensities

## Parameters:

- $q_j(0)$  Initial propensity
- $\square$  Experimentation
- $\square$  Recency (forgetting)

## Variables:

- $a_j$  Current action choice
- $q_j$  Propensity for action  $a_j$
- $a_k$  Last action chosen
- $r_k$  Reward for action  $a_k$
- $t$  Current time step
- $N$  Number of actions

$$q_j(t + 1) = [1 - \phi]q_j(t) + E_j(\square, N, k, t)$$

$$E_j(\square, N, k, t) = \begin{cases} r_k(t)[1 - \epsilon] & \text{if } j = k \\ q_j(t) \frac{\epsilon}{N-1} & \text{if } j \neq k \end{cases}$$

# From Propensities to Probabilities

## Example: Gibbs-Boltzmann Probability

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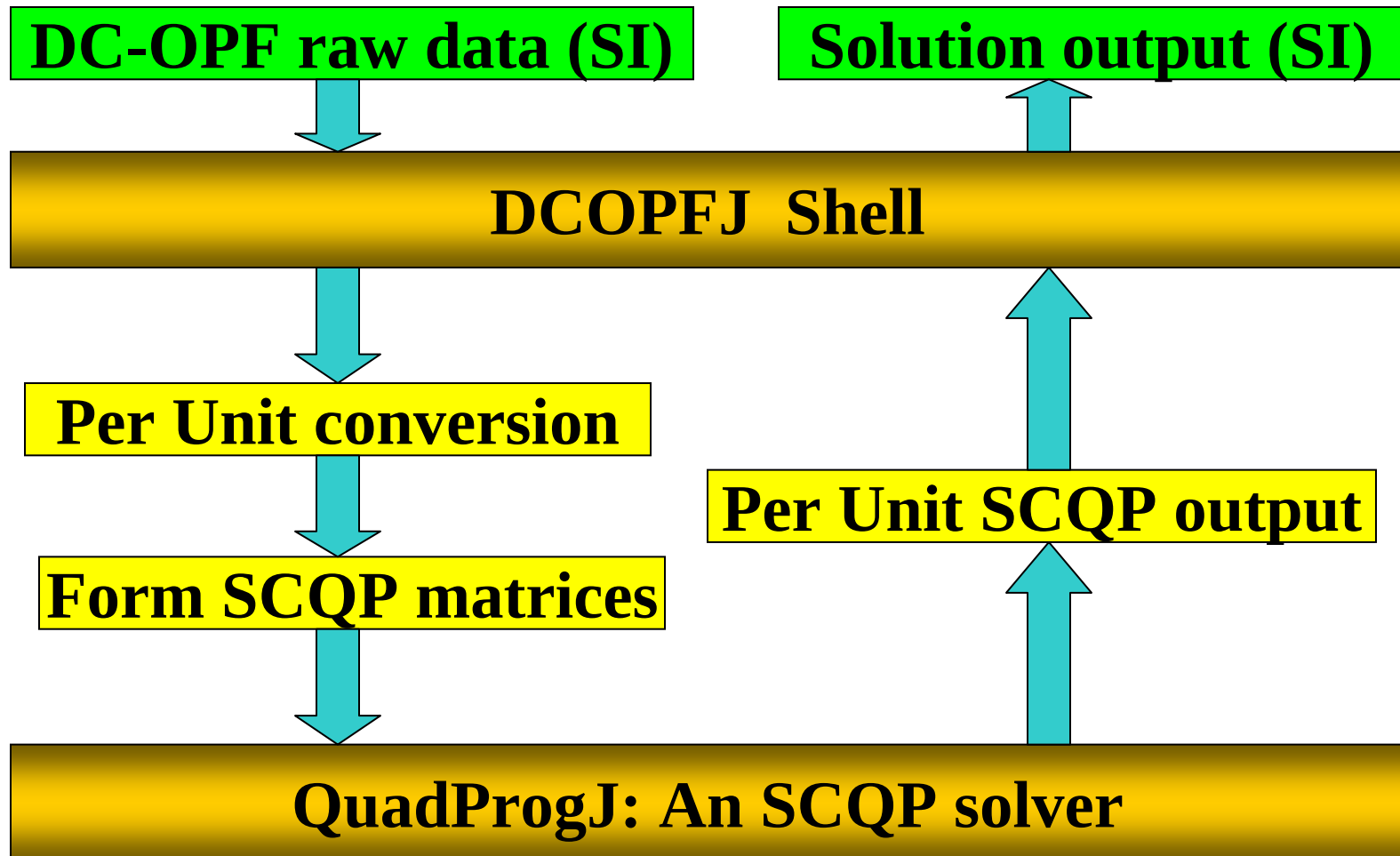
- $q_j(t)$  = "propensity" to choose action  $j$  at time  $t$
- $N$  = Total number of available actions
- $T$  = Temperature ("cooling") parameter
- $\text{Prob}_j(t)$  = Probability of choosing action  $j$  at time  $t$

$$\text{Prob}_j(t) = \frac{e^{q_j(t)/T}}{\sum_{n=1}^N e^{q_n(t)/T}}$$

# DCOPFJ: DC-OPF Solver for AMES ISO

Sun/Tesfatsion, *Proceedings, IEEE PES GM*, 2007

[www.econ.iastate.edu/tesfatsi/DCOPFJHome.htm](http://www.econ.iastate.edu/tesfatsi/DCOPFJHome.htm)



# DCOPFJ Implementation for AMES V1.31

Gen-reported  
total variable  
costs

Generators report supply offers and  
LSEs report 100%-fixed demand bids  
to ISO for day-ahead market

Voltage angle  
for node k

Minimize  $\sum_{i=1}^I [a_i^R p_{Gi} + b_i^R p_{Gi}^2] + \pi \left[ \sum_{km \in BR} [\delta_k - \delta_m]^2 \right]$

w.r.t.  $p_{Gi}, i = 1, \dots, I; \delta_k, k = 1, \dots, K$

Power level for  
Generator  $i=1, \dots, I$

subject to

Balance constraints:

Shadow price for node k balance  
constraint gives LMP for node k

Fixed demand  
bid (load) for  
LSE j

$$0 = \sum_{j \in J_k} p_{Lj} - \sum_{i \in I_k} p_{Gi} + \sum_{km \text{ or } mk \in BR} B_{km} (\delta_k - \delta_m)$$

Branch flow (thermal) constraints:

$$|B_{km} (\delta_k - \delta_m)| \leq P_{km}^U$$

Reported generator capacity constraints:

$$Cap_i^L \leq p_{Gi} \leq Cap_i^{RU}$$

Shadow price for  
each inequality  
constraint is also  
determined

Voltage angle setting at reference node 1:

$$\delta_1 = 0$$

## AMES V2.0: Extends AMES V1.31 by permitting LSEs to report fixed & price-sensitive demand bids to day-ahead market

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□ Hourly demand bid for any LSE  $j$  =  
(Fixed Demand Bid, Price-Sensitive Demand Bid)

- Fixed Demand Bid =  $p_{Lj}^F$  (in MWs)
- Price-Sensitive Demand Bid = Linear demand function for real power  $p_{Lj}^S$  (in MWs) over a purchase capacity interval :

$$D_j(p_{Lj}^S) = c_j - 2d_j p_{Lj}^S$$

$$0 \leq p_{Lj}^S \leq SLMax_j$$

# DCOPFJ Implementation for AMES V2.0

Generators report supply offers and LSEs report fixed & price-sensitive demand bids to ISO for day-ahead market

Minimize

LSE gross buyer surplus

Gen-reported  
total variable  
costs

$$\sum_{i=1}^I [a_i^R p_{Gi} + b_i^R p_{Gi}^2] - \sum_{j=1}^J [c_j^S p_{Lj} - d_j^S p_{Lj}^2] + \pi \left[ \sum_{km \in BR} [\delta_k - \delta_m]^2 \right]$$

w.r.t.  $p_{Gi}, i = 1, \dots, I; p_{Lj}^S, j = 1, \dots, J; \delta_k, k = 1, \dots, K$

Subject to

$$\sum_{i \in I_k} p_{Gi} - \sum_{j \in J_k} (p_{Lj}^F + p_{Lj}^S) - \sum_{km \text{ or } mk \in BR} B_{km} [\delta_k - \delta_m] = 0$$

$$|B_{km} [\delta_k - \delta_m]| \leq P_{km}^U$$

Fixed and price-  
sensitive demand  
bids for LSE j

$$Cap_i^L \leq p_{Gi} \leq Cap_i^{RU}$$

Purchase capacity  
interval for LSE j

$$0 \leq p_{Lj}^S \leq SLMax_j$$

$$\delta_1 = 0$$

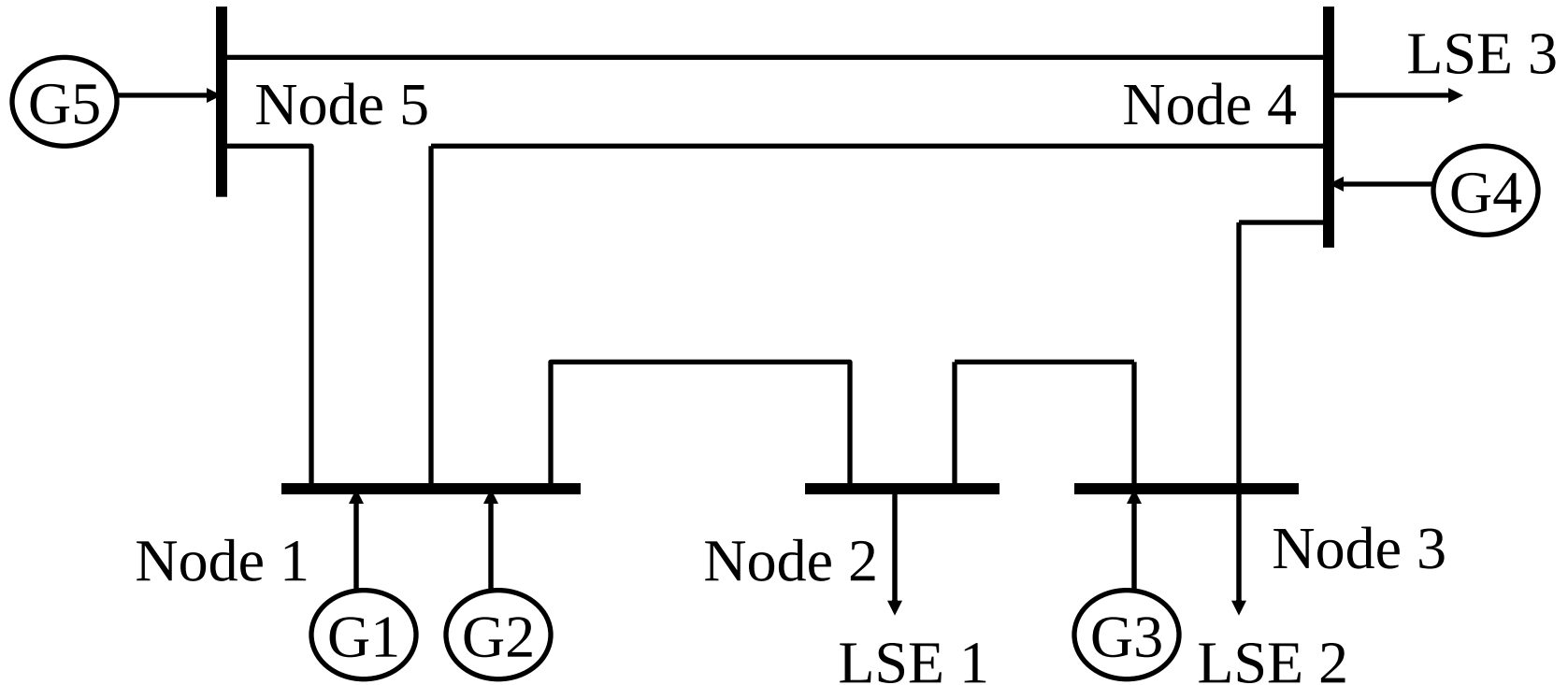
# Illustrative Experimental Findings Using AMES Version 2.0

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- ★ H. Li, J. Sun, and L. Tesfatsion, “Dynamic LMP Response Under Alternative Price-Cap and Price-Sensitive Demand Scenarios”  
*Proceedings, IEEE Pow. Eng. Soc. GM, Pittsburgh, July 2008, to appear,*  
[www.econ.iastate.edu/tesfatsi/DynamicLMPResponse.IEEEPE2008.LST.pdf](http://www.econ.iastate.edu/tesfatsi/DynamicLMPResponse.IEEEPE2008.LST.pdf)
- ★ Focus of Paper: Dynamic LMP response and market performance under alternative treatments for:
  - price-sensitivity of LSE demand bids (0 to 100%)
  - learning capabilities (absent or present)
  - supply-offer price cap (high, moderate, or low)

| Age Group | Percentage |
|-----------|------------|
| 18-24     | 10%        |
| 25-34     | 20%        |
| 35-44     | 30%        |
| 45-54     | 25%        |
| 55-64     | 15%        |
| 65-74     | 10%        |
| 75-84     | 5%         |
| 85+       | 5%         |

- Extension of static test case (by John Lally)  
used in ISO-NE/PJM training materials



## Grid/Gen/Load Data for Benchmark Case: No Price-Sensitive Demand, No Gen Learning, and No Supply-Offer Price Cap

|                          |         |                      |        |        |                  |                  |        |        |        |
|--------------------------|---------|----------------------|--------|--------|------------------|------------------|--------|--------|--------|
| Base Values <sup>a</sup> |         |                      |        |        |                  |                  |        |        |        |
| $S_o$                    | $V_o$   |                      |        |        |                  |                  |        |        |        |
| 100                      | 10      |                      |        |        |                  |                  |        |        |        |
| $K^b$                    | $\pi^c$ |                      |        |        |                  |                  |        |        |        |
| 5                        | 0.05    |                      |        |        |                  |                  |        |        |        |
| Branch<br>From           | To      | lineCap <sup>d</sup> | $X^e$  |        |                  |                  |        |        |        |
| 1                        | 2       | 250.0                | 0.0281 |        |                  |                  |        |        |        |
| 1                        | 4       | 150.0                | 0.0304 |        |                  |                  |        |        |        |
| 1                        | 5       | 400.0                | 0.0064 |        |                  |                  |        |        |        |
| 2                        | 3       | 350.0                | 0.0108 |        |                  |                  |        |        |        |
| 3                        | 4       | 240.0                | 0.0297 |        |                  |                  |        |        |        |
| 4                        | 5       | 240.0                | 0.0297 |        |                  |                  |        |        |        |
| Gen ID                   | atNode  | FCost                | $a$    | $b$    | Cap <sup>L</sup> | Cap <sup>U</sup> | Init\$ |        |        |
| 1                        | 1       | 1600.0               | 14.0   | 0.005  | 0.0              | 110.0            | \$1M   |        |        |
| 2                        | 1       | 1200.0               | 15.0   | 0.006  | 0.0              | 100.0            | \$1M   |        |        |
| 3                        | 3       | 8500.0               | 25.0   | 0.010  | 0.0              | 520.0            | \$1M   |        |        |
| 4                        | 4       | 1000.0               | 30.0   | 0.012  | 0.0              | 200.0            | \$1M   |        |        |
| 5                        | 5       | 5400.0               | 10.0   | 0.007  | 0.0              | 600.0            | \$1M   |        |        |
| LSE<br>ID                | atNode  | L-00 <sup>f</sup>    | L-01   | L-02   | L-03             | L-04             | L-05   | L-06   | L-07   |
| 1                        | 2       | 350.00               | 322.93 | 305.04 | 296.02           | 287.16           | 291.59 | 296.02 | 314.07 |
| 2                        | 3       | 300.00               | 276.80 | 261.47 | 253.73           | 246.13           | 249.93 | 253.73 | 269.20 |
| 3                        | 4       | 250.00               | 230.66 | 217.89 | 211.44           | 205.11           | 208.28 | 211.44 | 224.33 |
| ID                       | atNode  | L-08                 | L-09   | L-10   | L-11             | L-12             | L-13   | L-14   | L-15   |
| 1                        | 2       | 358.86               | 394.80 | 403.82 | 408.25           | 403.82           | 394.80 | 390.37 | 390.37 |
| 2                        | 3       | 307.60               | 338.40 | 346.13 | 349.93           | 346.13           | 338.40 | 334.60 | 334.60 |
| 3                        | 4       | 256.33               | 282.00 | 288.44 | 291.61           | 288.44           | 282.00 | 278.83 | 278.83 |
| ID                       | atNode  | L-16                 | L-17   | L-18   | L-19             | L-20             | L-21   | L-22   | L-23   |
| 1                        | 2       | 408.25               | 448.62 | 430.73 | 426.14           | 421.71           | 412.69 | 390.37 | 363.46 |
| 2                        | 3       | 349.93               | 384.53 | 369.20 | 365.26           | 361.47           | 353.73 | 334.60 | 311.53 |
| 3                        | 4       | 291.61               | 320.44 | 307.67 | 304.39           | 301.22           | 294.78 | 278.83 | 259.61 |

<sup>a</sup>For simplicity, the base apparent power  $S_o$  (MVA) and base voltage  $V_o$  (kV) are chosen so base impedance  $Z_o$  satisfies  $Z_o = V_o^2/S_o = 1$ .

<sup>b</sup>Total number of nodes

<sup>c</sup>Soft penalty weight  $\pi$  for voltage angle differences

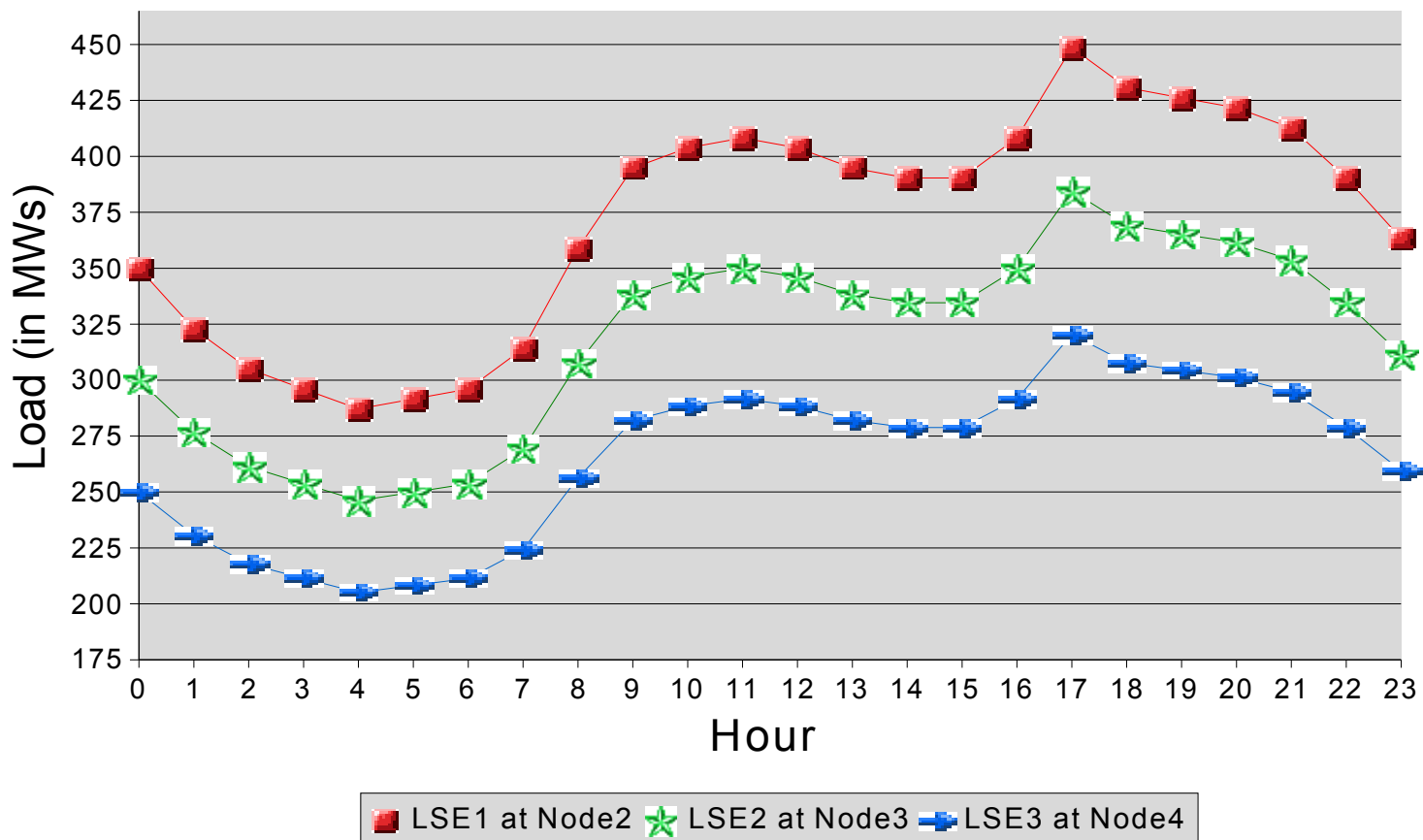
<sup>d</sup>Upper limit  $P_{km}^U$  (in MWs) on the magnitude of real power flow in branch  $km$

<sup>e</sup>Reactance  $X_{km}$  (in ohms) for branch  $km$

<sup>f</sup>L-H: Load (in MWs) for hour H, where H=00,01,...,23

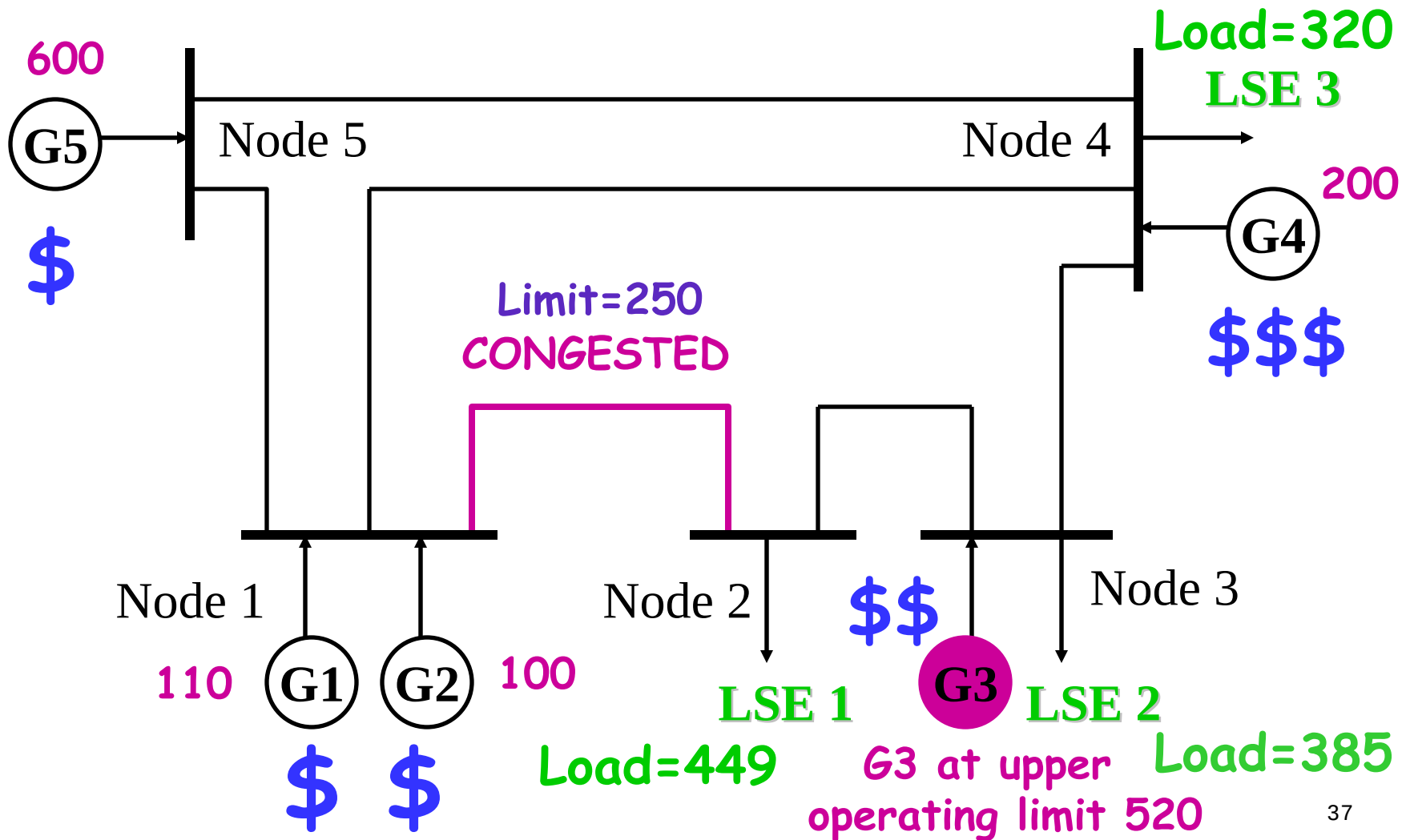
# Daily LSE Load Profiles

Benchmark Case: No Price-Sensitive Demand,  
No Gen Learning, and No Supply-Offer Price Cap



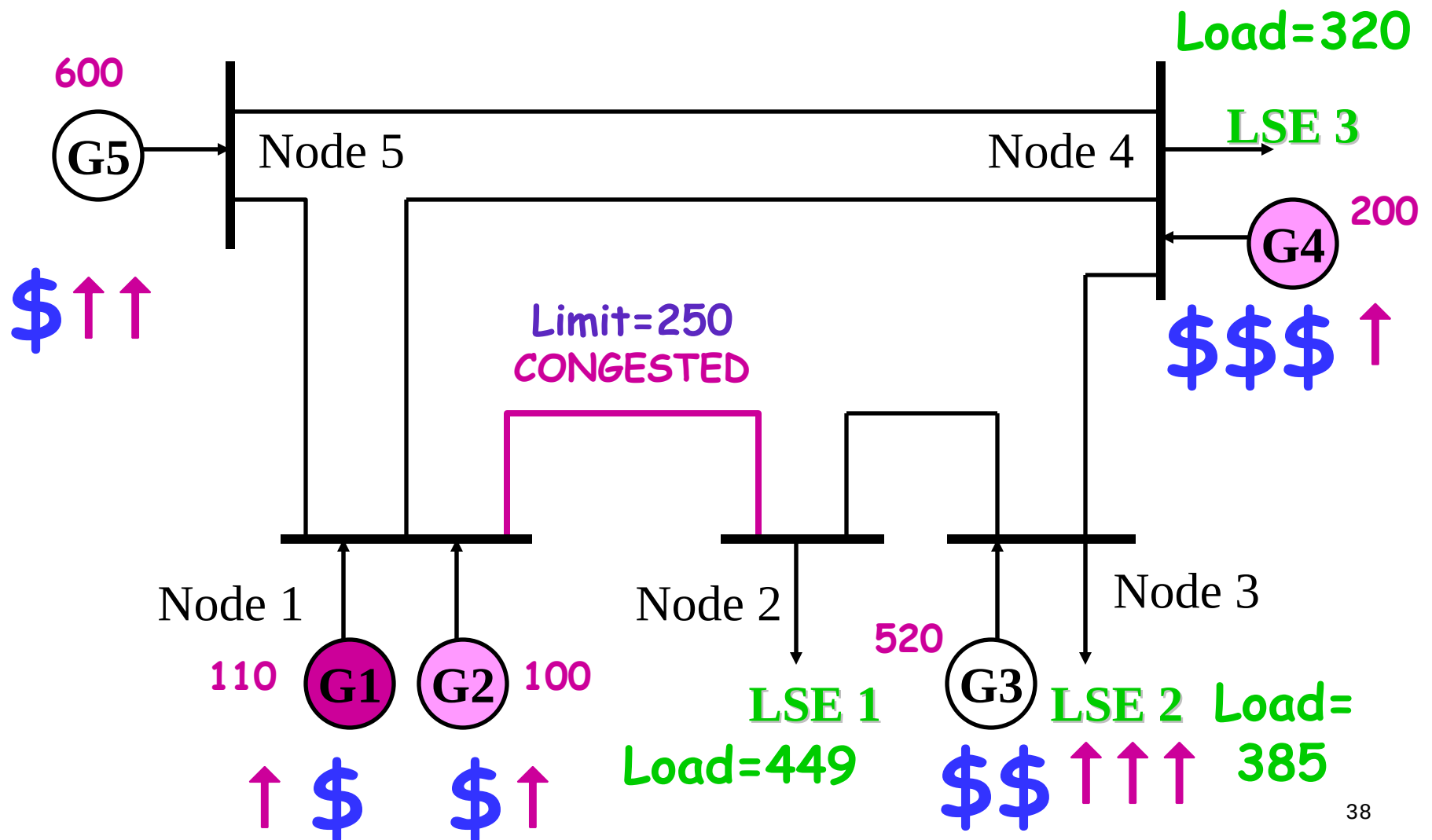
# Peak Hour-17 Outcomes with No Gen Learning

Generators report true cost/capacity conditions to ISO

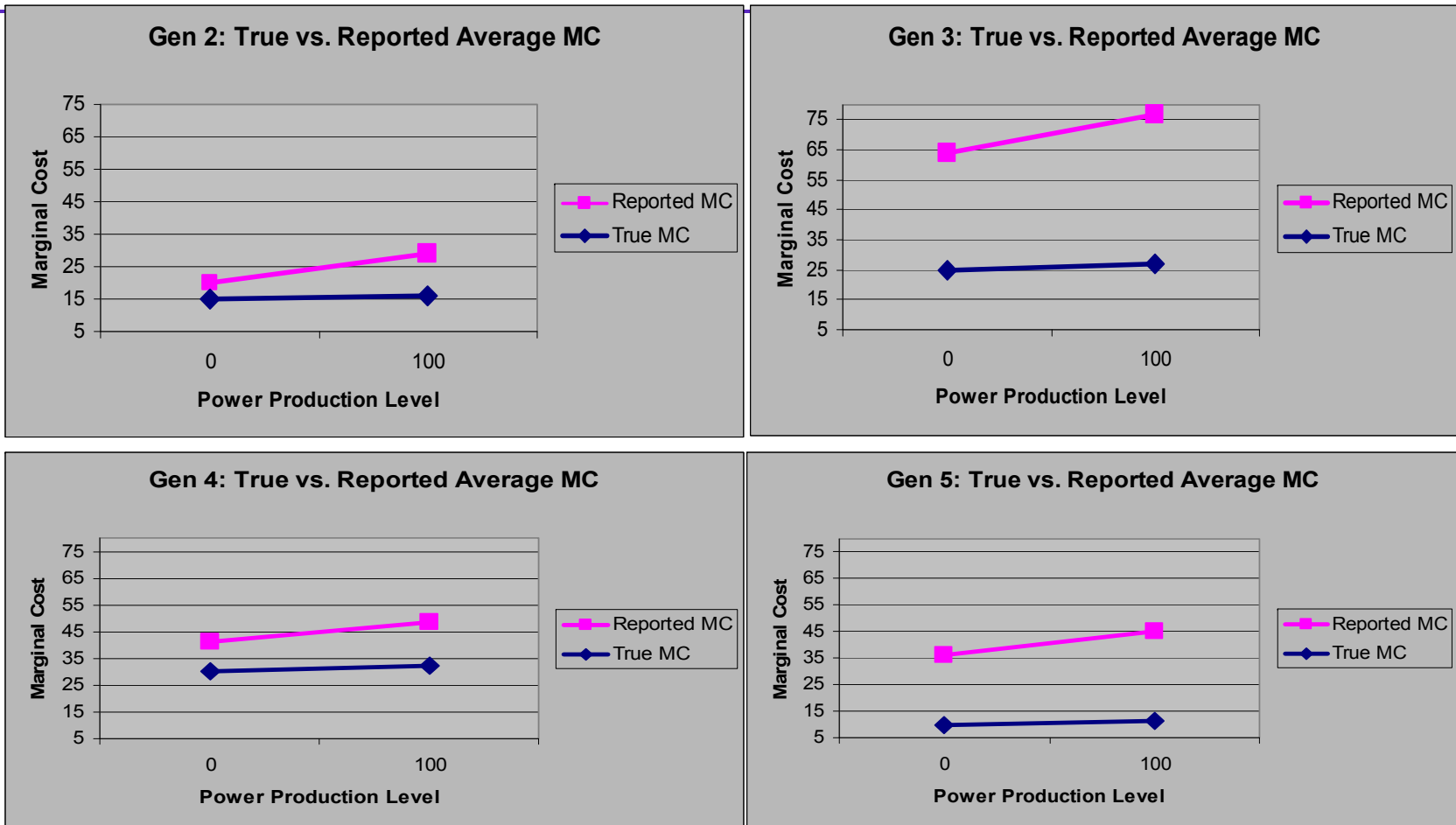


# Peak Hour-17 Outcomes (Day 422) With VRE Gen Learning

(By Day 422, each generator has converged to one supply offer choice with Prob  $\geq 0.999$ )



# True Vs. Reported MC (Averaged)\* on Day 422 (Each Generator has converged with Prob $\geq 0.999$ )



\*NOTE: 20-run averages. Typical convergence time = 62 days, max time = 422. Omitted Gen 1 MC curve is similar to Gen 2's.

## Dynamic 5-Node Test Case Results With 100% Fixed LSE Demand Bids (Load Profiles)

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### ★ BOTTOM LINE:

Using only simple VRE reinforcement learning, generators quickly learn to tacitly collude on *higher prices*.

## Construction of a Ratio Measure (R) for Relative Demand-Bid Price Sensitivity

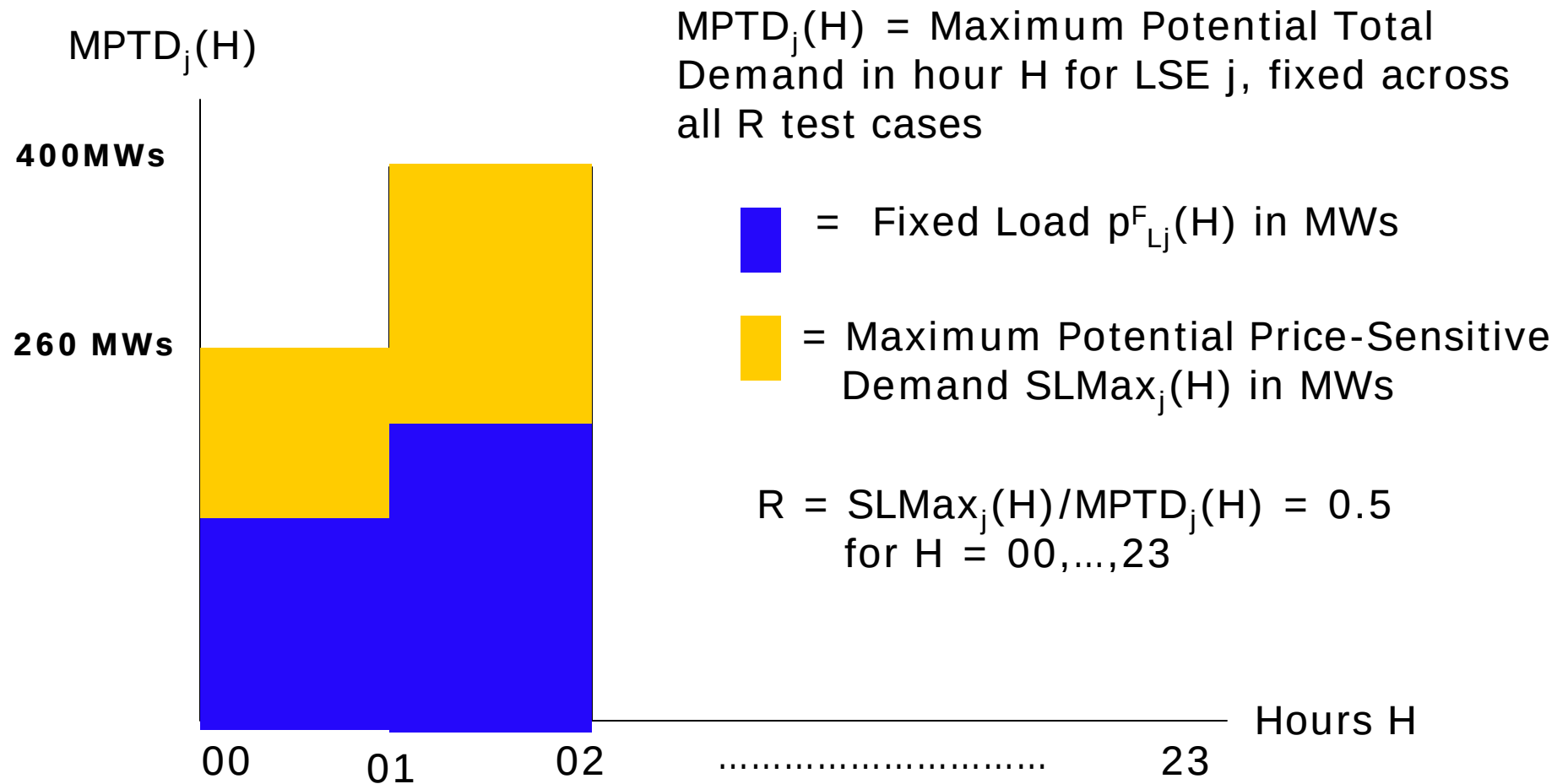


**TABLE II**  
**AVERAGE EFFECTS OF R CHANGES WITH NO SUPPLY-OFFER PRICE CAP**  
**(No PCap) AND NO GENERATOR LEARNING**

**Lerner Index**

| R   | Avg LMP | Avg Total Demand | Avg Op Cost | Avg LI |
|-----|---------|------------------|-------------|--------|
| 0.0 | 25.18   | 318.21           | 3779.17     | 0.0056 |
| 0.1 | 24.51   | 299.19           | 3439.32     | 0.0042 |
| 0.2 | 23.92   | 279.69           | 3100.91     | 0.0036 |
| 0.3 | 23.33   | 259.85           | 2765.58     | 0.0032 |
| 0.4 | 22.72   | 240.18           | 2446.54     | 0.0029 |
| 0.5 | 22.10   | 220.88           | 2143.65     | 0.0026 |
| 0.6 | 21.35   | 204.09           | 1888.46     | 0.0022 |
| 0.7 | 20.49   | 188.67           | 1662.19     | 0.0013 |
| 0.8 | 19.49   | 175.74           | 1481.15     | 0.0000 |
| 0.9 | 18.27   | 169.68           | 1408.55     | 0.0000 |
| 1.0 | 17.04   | 163.87           | 1349.49     | 0.0000 |

**R=0.0 → 100% Fixed Demand; R=1.0 → 100% Price-Sensitive Demand**

**TABLE III**  
**AVERAGE EFFECTS (WITH STANDARD DEVIATIONS) OF R CHANGES WITH**  
**NO PCAP AND WITH GENERATOR LEARNING**

**VRE**

| R   | Avg LMP           | Avg Total Demand | Avg Op Cost         | Avg LI   |
|-----|-------------------|------------------|---------------------|----------|
| 0.0 | * 70.10<br>(3.14) | 318.21<br>(0.00) | 9198.63<br>(125.88) | 0.5692 * |
| 0.1 | * 73.84<br>(3.24) | 286.39<br>(0.00) | 8450.26<br>(444.20) | 0.5755 * |
| 0.2 | * 81.46<br>(2.85) | 254.57<br>(0.05) | 7629.94<br>(298.22) | 0.5933 * |
| 0.3 | 72.67<br>(3.02)   | 223.84<br>(1.14) | 5501.09<br>(228.62) | 0.5433   |
| 0.4 | 39.43<br>(1.16)   | 198.70<br>(2.03) | 3300.37<br>(172.36) | 0.4341   |
| 0.5 | 35.75<br>(0.48)   | 170.75<br>(2.42) | 2717.73<br>(157.73) | 0.4185   |
| 0.6 | 33.52<br>(0.41)   | 155.47<br>(2.86) | 2259.65<br>(135.01) | 0.3660   |
| 0.7 | 28.73<br>(0.60)   | 145.84<br>(4.23) | 1877.91<br>(151.64) | 0.2815   |
| 0.8 | 26.75<br>(0.54)   | 133.99<br>(4.96) | 1627.45<br>(157.23) | 0.2547   |
| 0.9 | 25.09<br>(0.51)   | 120.17<br>(5.43) | 1388.31<br>(132.60) | 0.2342   |
| 1.0 | 23.23<br>(0.48)   | 108.51<br>(5.80) | 1184.18<br>(125.88) | 0.2078   |

**R=0.0 → 100% Fixed Demand; R=1.0 → 100% Price-Sensitive Demand**

## Dynamic 5-Node Test Case Results with Price-Sensitive Demand Bids

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### ★ BOTTOM LINE:

Even with 100% price-sensitive  
demand bids ( $R=1.0$ ), Avg LMP is  
*much higher under VRE learning !*

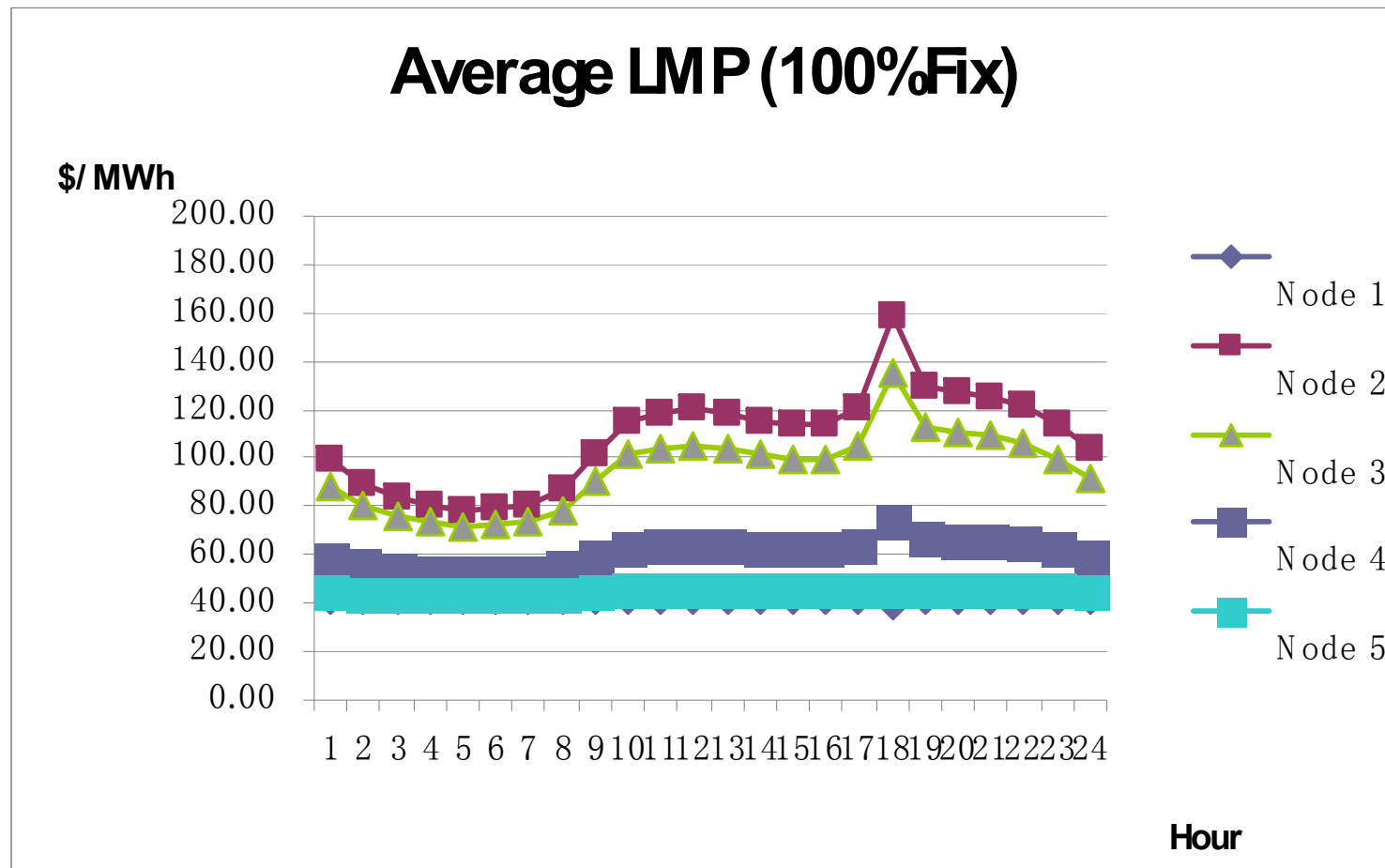
## Dynamic 5-Node Test Case Results for LMP Under Alternative Supply-Offer Price Caps

AVERAGE LMP EFFECTS (WITH STANDARD DEVIATIONS) OF CHANGES IN  
PCAP WITH NO DEMAND-BID PRICE SENSITIVITY ( $R=0.0$ )

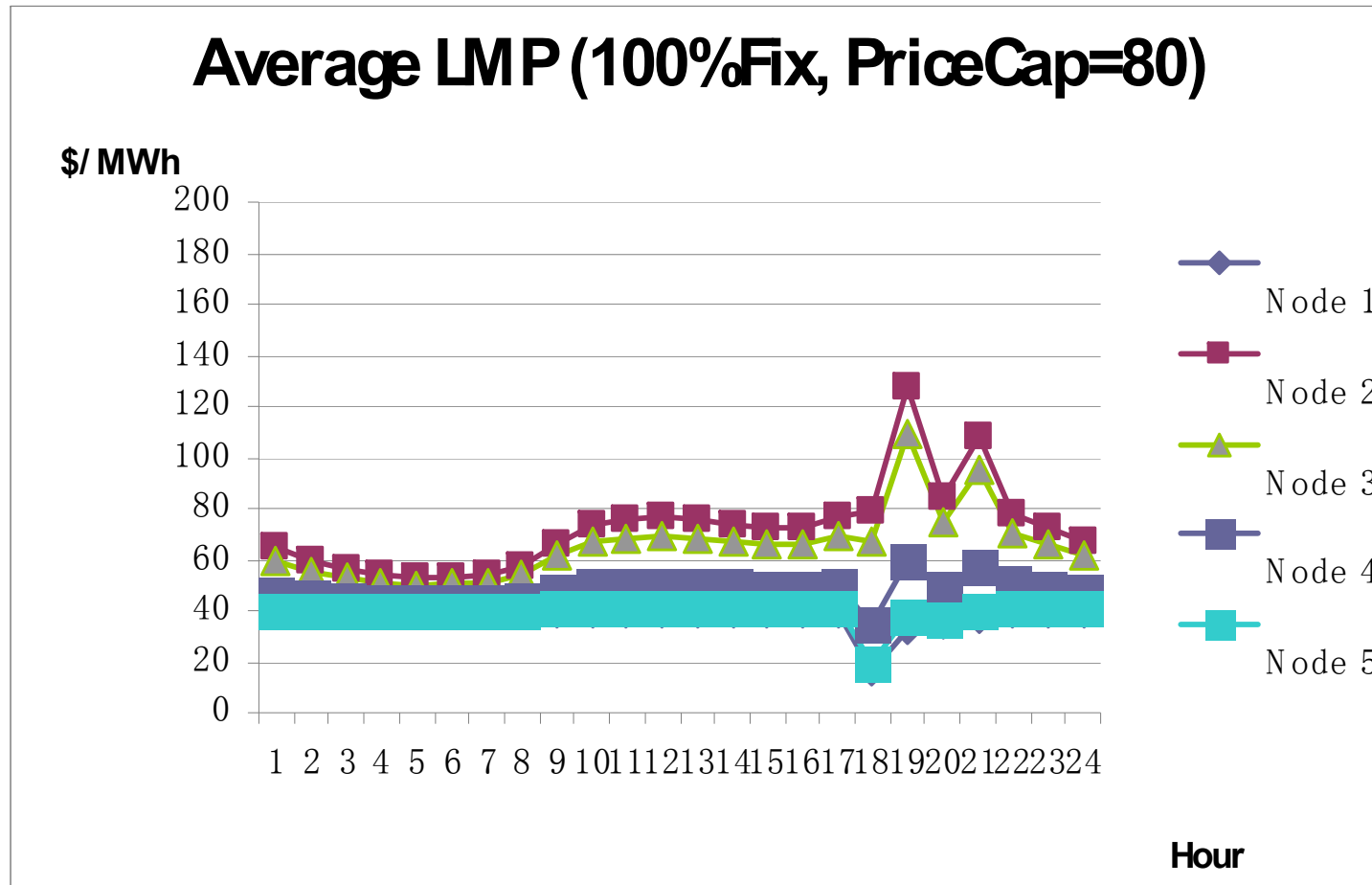
|                                 | No PCap         | PCap=120        | PCap=100        | PCap=80         |
|---------------------------------|-----------------|-----------------|-----------------|-----------------|
| Avg LMP with<br>No Gen Learning | 25.18           | 25.18           | 25.18           | 25.18           |
| Avg LMP with<br>Gen Learning    | 70.10<br>(3.14) | 65.72<br>(4.01) | 58.00<br>(1.51) | 54.96<br>(2.41) |

VRE

# No Price Cap Case: No PCap, R=0.0, & With VRE Gen Learning

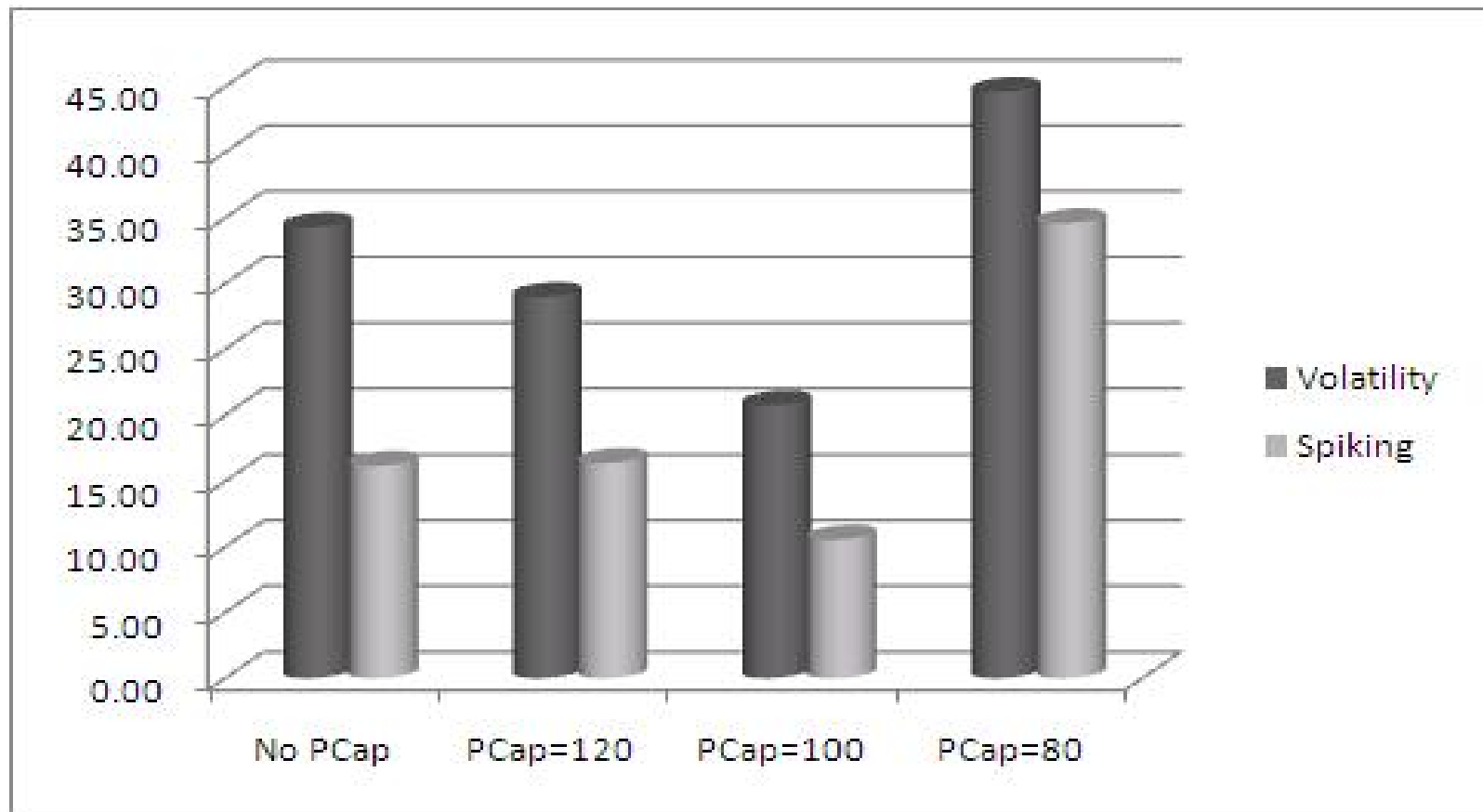


## Low Price-Cap Case: PCap=80, R=0.0, & With VRE Gen Learning



# LMP Spiking/Volatility Under Varied Price Caps

With 100% Fixed Demand ( $R=0.0$ ) & VRE Gen Learning



## Dynamic 5-Node Test Results for Price Caps with 100% Fixed Demands and VRE Gen Learning

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### ★ BOTTOM LINE:

Strongly binding supply-offer price caps  
can *increase* LMP spiking and volatility  
around peak-demand hours even though  
Average LMP declines!

# Conclusions

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- \* **Restructured wholesale power markets** are complex mixtures of physical constraints, institutional arrangements, and strategic human participants.
- \* **Agent-based test beds** permit the systematic dynamic study of such systems through intensive computational experiments.
- \* For increased empirical validity, test beds should be **iteratively developed** with ongoing input from actual market participants.
- \* To increase usefulness for research/teaching/training and to aid knowledge accumulation, these test beds should be **open-source**.

# On-Line Resources

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- ❑ H. Li, J. Sun, and L. Tesfatsion, "Dynamic LMP Response Under Alternative Price-Cap and Price-Sensitive Demand Scenarios" *Proceedings, IEEE PES GM, Pittsburgh, July 2008, to appear*  
[www.econ.iastate.edu/tesfatsi/DynamicLMPResponse.IEEEPES2008.LST.pdf](http://www.econ.iastate.edu/tesfatsi/DynamicLMPResponse.IEEEPES2008.LST.pdf)
- ❑ AMES Market Package Homepage (Code/Manuals/Pubs)  
[www.econ.iastate.edu/tesfatsi/AMESMarketHome.htm](http://www.econ.iastate.edu/tesfatsi/AMESMarketHome.htm)
- ❑ Agent-Based Electricity Market Research  
[www.econ.iastate.edu/tesfatsi/aelectric.htm](http://www.econ.iastate.edu/tesfatsi/aelectric.htm)
- ❑ Open-Source Software for Electricity Market Research, Teaching, and Training  
[www.econ.iastate.edu/tesfatsi/ElectricOSS.htm](http://www.econ.iastate.edu/tesfatsi/ElectricOSS.htm)