NSF Energy Project: Overview

"Decision Models for Bulk Energy Transportation Networks"

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<u>Context</u>:

This work targets what we call the National Electric Energy System (NEES), which is comprised of physical infrastructure, industrial and governmental organizations, individual and corporate decision-making entities, and associated information processing systems for

- Electric generation and bulk transmission systems
- Natural gas production and pipeline systems

- Coal production and rail/barge transportation systems
- Water reservoirs and hydroelectric production systems
- Influence of carbon dioxide, sulfur dioxide, and nitrogen oxide constraints
- Markets and market agents which comprise economic systems for bulk energy trading

Objective:

The objective of this research is to develop two complementary and related classes of decision models, a structural model & a behavioral model, for the ultimate purpose of addressing the following issues:

National Scale (federal government, NERC):
(1) Possible improvements in energy flow patterns
(2) Effects of catastrophic events
(3) Detection of physical infrastructure weaknesses
(4) Detection of weaknesses in institutional arrangements
(5) Infrastructure enhancements to improve performance
(6) Effects of environmental regulations on energy system performance

Regional Scale (regional independent system operator):
(1) Effects of market design on market (energy system?) performance
(2) Sensitivity of market performance to system shocks
(3) Potential improvements in market design

Local Scale (local electric utility company):
(1) Effects of changes in raw fuel production and transportation on the returns from investing in specific types of plants at specific locations
(2) Response of energy buyers and sellers to potential new policies designed to improve transparency and ease of trade

We are developing two complementary and related classes of decision models, a structural model and an agent-based behavioral model, as illustrated in Fig. 1. Progress on the structural model is described in Section A. Progress on the behavioral model is described in Section B. Progress on integration of the two models is described in Section C. An effort to understand impediments to transmission line investment is described in Section D.

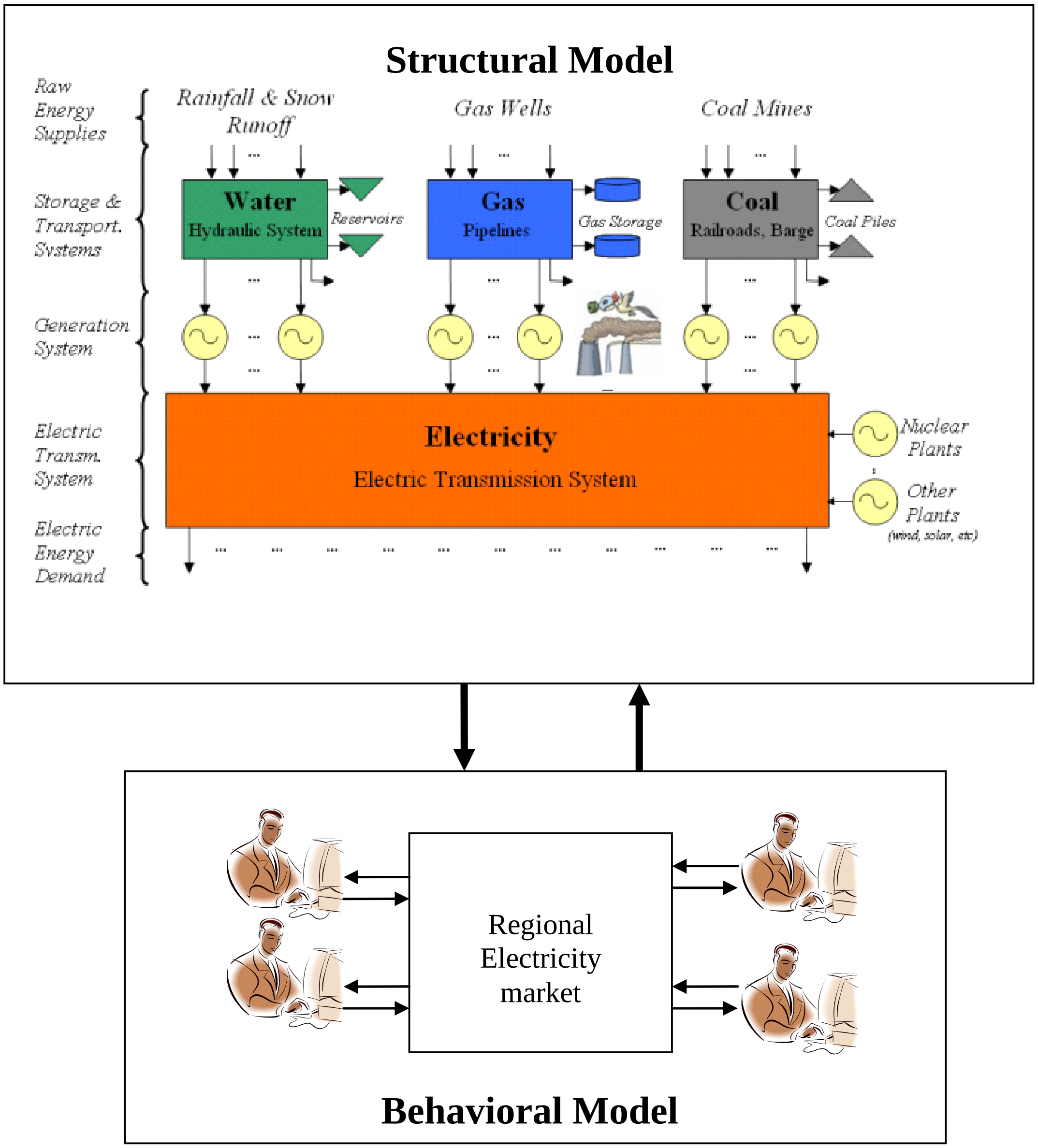

Fig. 1: Interaction of structural and behavioral model

A. Structural Model:

The structural model is based on a generalized network flow model that captures the gas, coal, and water production, storage, and transportation systems and the electricity generation and transmission systems, at a national level. The top part of Fig. 1 provides conceptual illustration of the structural model.

The structural model simulates the national energy system. Simulation times are in the order of few months to several years. An important element of the structural model is its ability to integrate the four different energy subsystems (electric, coal, gas, water) in a single model. A key model attribute that facilitates this within our network flow model is the ability to model different portions of the energy system with varying levels of time-step granularity. Figure A.1 illustrates. Input data to the model includes topology (nodes, arcs), supply and demand at gas and coal supply points and electric demand points, respectively, per unit energy flow cost along each arc, and arc capacities and efficiencies, all at each time *t*. We developed aggregated topologies to represent the national US energy system.

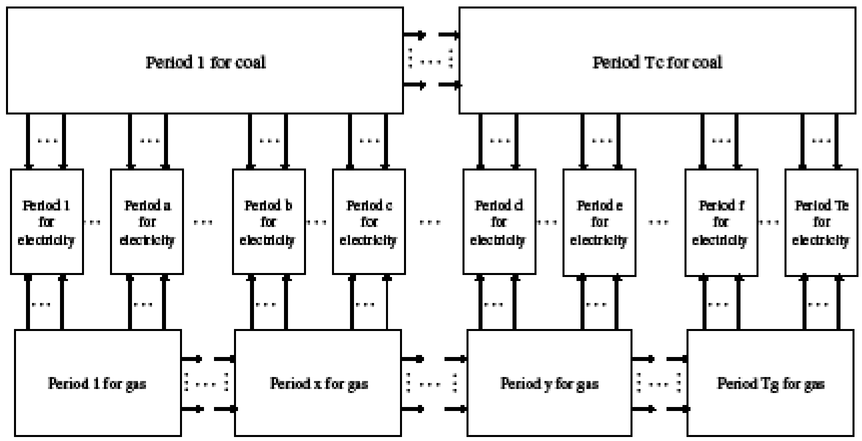

Fig. A.1: Varying Time-Step Modeling for Coal, Gas, Electricity

The model is solved as the generalized network simplex algorithm (a specialized linear program), which is extremely efficient, capable of handling very high-dimensional problems. We use CPLEX to implement the solutions.

There have been two main areas of progress regarding the structural model during the past year. The first focused on modeling catastrophic events, using 2005 NEES data. The second focused on treatment of uncertainty, using 2006 NEES data. These areas are described in Sections A.1 and A.2 below.

A.1 Modeling catastrophic events

We used the 2005 Katrina/Rita hurricane events to motivate our effort to model and study catastrophic events on the NEES. To this end, several modeling improvements were made relative to what was done in our previous work [A1-1, A1-2], a very large data gathering effort was performed, and valiadation studies were implemented. This work is reported in [A1-3]. This work is supervised by Dr. McCalley.

A.1.1: Modeling Improvements:

The modeling improvements are summarized below:

1. Modeling the demand not served: The use of network linear programming to obtain a minimum-cost pattern of energy movements makes the implicit assumption that the model is able to satisfy the demand. However, due to the effects of a major contingency, the network simplex algorithm used for simulation may not be able to find a feasible solution to the optimization problem. In other words, it may be the case that there is not feasible flow able to either locally or globally satisfy the demand

either of electricity or of coal and natural gas for uses other than electricity generation. To overcome the possibility of infeasible solutions, some adjustments to the network model are necessary. The solution implemented is to add a dummy supply node connected to all the electricity and natural gas transshipment nodes by arcs having unlimited capacity in order to satisfy any possible demand.

2. Modeling sequential decisions: In the network model developed in our previous work [1], decisions variables (flows) for every time step are determined simultaneously, that is, the optimization process treats the entire multi-time-period network as a single static network and finds the optimal way to satisfy the demands on that network. This approach implies prior knowledge on any changes in the network parameters, such as the reduction on the capacity of one or more arcs as a result of a disruption. A simple approach to address this issue consists of decoupling the network so that the pre and post contingency decisions are independent. This independence can be achieved by eliminating the arc corresponding to the storage carried out from the period immediately before the contingency and the period immediately after the contingency, and adjusting the demands on the corresponding storage nodes accordingly.
3. Improvements in the demand model: There were two improvements:
    a. Elasticity: The energy demand is highly inelastic with respect to prices, so the assumption of inelastic demand as considered in our previous model is appropriate under normal operating conditions. However, under the effects of a major contingency, congestion may lead to large price peaks either locally or globally, and the prices may increase so much that the assumption of demand inelasticity may not hold true. A practical consideration is that with elastic demand the network problem will no longer be linear since the value of an elastic demand would depend on the dual solution of the generalized minimum cost flow problem and thus the optimal solution can not be obtained in a single iteration as done in our previous work. A demand response mechanism was implemented as part of an iterative process to take into account the effect of elasticity. The first iteration uses an initial estimate for the demands at the transshipment node, then solves the problem using the network simplex algorithm, and finally, determines a first estimate for the nodal prices from the dual solution. Before the second run of the network simplex algorithm, the demand response mechanism takes place and new demands are calculated by computing the product of the percent increase in nodal prices (with respect to a base case) and the values for elasticity. With the new values for the demands, a new solution is obtained by using the network simplex algorithm. The process is repeated until convergence.
    b. Decomposition by demand levels: Simulations in the network model provide results that are aggregated for each time step. That is, energy flows and nodal prices within a given time step are aggregated into a single value, and any variability in the system variables occurring within a time step is lost. The time step used in previous work (a month) might not reflect some effects and interactions that may be important when studying the effects of disruptions, like for example system congestion or price spikes that are especially noticeable during periods of high load. Moreover, since gas fired generation is

more expensive than coal-fired generation, typically many natural gas power plants do not operate continuously but only on periods of high demand. If the model is not able to represent periods when high demand occurs, then in the simulation results some of the more expensive generating units will never be used. The consequences of not modeling variation of load level are inaccuracy on the calculation of electricity prices, congestion levels, and fossil fuel use. To solve this issue, the demand for each month and for each node is decomposed as illustrated in Figure A.2.

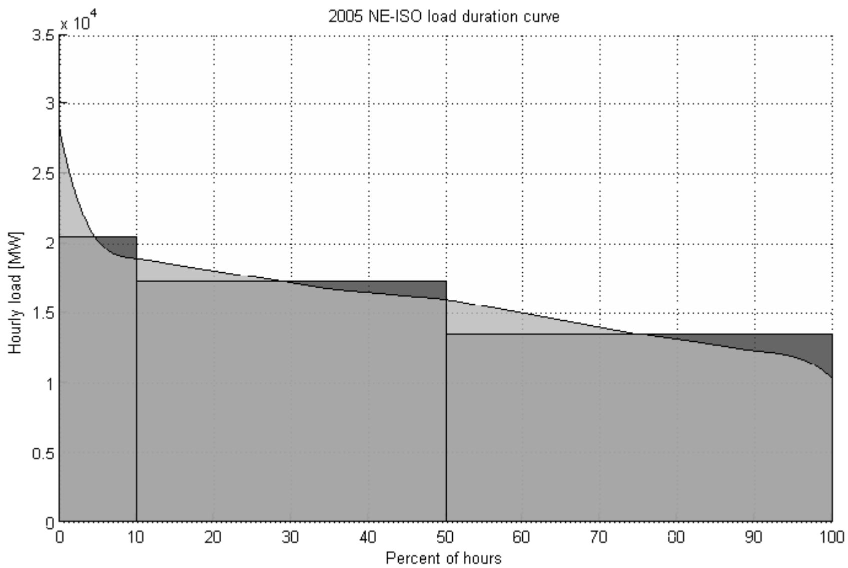

Figure A.2: Load decomposition

A.1.2 Data gathering

Data was gathered for the electric, natural gas, and coal bulk production and transportation sub-systems. The data reflects the hurricane's effects in terms of changes in production, transportation, storage, and prices of different energy forms. Where possible, data was gathered to reflect conditions given months or years before and for the months following the hurricanes. Data sources include daily situation reports by the Department of Energy's Office of Electricity Delivery and Energy Reliability (OE), Energy Information Administration (EIA), Louisiana Public Services Commission, North America Electric Reliability Council (NERC), Mineral Management Service (MMS), Office of Pipeline Safety (OPS), Pipeline and Hazardous Materials Safety Administration (PHMSA), and on-site interviews, news releases, and financial releases offered by energy companies affected by the hurricanes. These data are summarized at http://home.eng.iastate.edu/~jdm/katrina/.

A.1.3 Validation studies

Validation of an earlier version of the NEES network model using 2002 data was carried out and reported in [2], where the reference case was designed with the actual configuration of generation and loads reported on a monthly basis for the year 2002. That is, coal-fired net generation and gas-fired net generation for each region and for each time step were fixed, together with the total emissions for 2002. This approach validated the model's ability to replicate fuel production and transportation to the generators. This validation effort reported aggregated simulation results, with annual total flows and annual average prices.

In the more recent validation effort using the 2005 data (as described in the previous section), instead of fixing all generation as in the 2002 case, only the loads and the total coal-fired net generation per month and per NERC region were fixed. Therefore optimization was performed on the coal, natural gas, and electricity flows. This reference case used for validation is less restrictive since it allows more freedom for the variables to change, especially the variables in the natural gas subsystem which were directly affected by the hurricanes in 2005. The purpose of this validation scheme is to test the ability of the model to reflect the effects of hurricanes Katrina and Rita in the U.S. energy system, and to capture how these effects (in terms of energy prices) propagated across time, space, and subsystems characterizing bulk energy transportation. Results of the simulation are compared to the corresponding actual values in Table A.1.

TABLE A.1: VALIDATION RESULTS FOR 2005 DATA

Result	Model	Actual	Difference
NG total production [Bcf]	17,200	18244*	-5.52%
NG imports from Canada [Bcf]	4,280	3,700	15.56%
NG production plus imports [Bcf]	21,480	21,944	-2.11%
Coal production [billion short ton]	1.08	1.128	-4.30%
NG consumed by electric sector [Bcf]	5,936	5,869	1.15%
NG consumed for uses other than power [Bcf]	14,500	14,500	0%
Gas-fired net generation [MWh]	712.63	757.97	-5.98%
Coal consumed by electric sector [billion short ton]	1	1.038	-3.66%
Cost of NG for electric power [$/Mcf]	9.02	8.49	6.20%
Cost of coal for electric power [$/short ton]	29.61	31.22	-5.20%
Electric energy price [$/MWh]	78.5	81.4	-3.60%

* Dry production

References for Section A.1

[A1-1] A. Quelhas, E. Gil, J. D. McCalley, and S. M. Ryan, "A Multiperiod Generalized Network Flow Model of the US Integrated Energy System: Part I—Model Description," *Power Systems, IEEE Transactions on*, vol. 22, pp. 829-836, 2007.
[A1-2] A. Quelhas and J. D. McCalley, "A Multiperiod Generalized Network Flow Model of the US Integrated Energy System: Part II—Simulation Results," *Power Systems, IEEE Transactions on*, vol. 22, pp. 837-844, 2007.
[A1-3] E. Gil and J. McCalley, "A US Energy System Model for Disruption Analysis: Validation Using Effects of 2005 Hurricanes," under review.

A.2 Treatment of uncertainty

Two main thrusts characterized this effort. In the first, a new set of data was gathered to model the 2006 NEES. In the second, a stochastic programming approach was implemented to capture influential uncertainties in the model. These two thrusts are described in Sections A.2.1 and A.2.2 below and published in [A1-1, A2-2]. This work is supervised by Dr. Ryan.

A.2.1 Data gathering for 2006 NEES model:

The entire data set for the bulk energy transportation network was comprehensively updated for the year 2006. This is a very labor-intensive process that requires accessing data from multiple online sources, followed by substantial processing to compute model parameters in the required format. We systematically verified those 2002 data that were still available, carefully documented the sources and processing involved, and created the corresponding 2006 data set. Some of the electricity subsystem topology changed due to reorganization of NERC regions between 2002 and 2006.

A.2.2 Stochastic modeling:

We investigated computational and approximation methods to improve the tractability of a stochastic program for incorporating fuel price and demand uncertainty in the bulk energy transportation network. These include decomposition, scenario aggregation and reduction, scenario sampling, and various combinations of these techniques. We used duality and complementarity concepts in stylized examples to illuminate reasons for the unexpected finding that uncertainty in natural gas prices could increase the proportion of electricity generated from natural gas rather than coal. We conducted a closer examination of the fuel network data to understand why some nodal prices for coal were higher than those for natural gas in the original 2002 data set.

Previously, we reported that in the optimal solution to the stochastic version of the bulk energy transportation model, more electricity was generated from natural gas as opposed to coal than in the deterministic version. Based on closer examination of nodal fuel prices and analysis of small, stylized instances of the same model, it now appears that the difference in the optimal fuel mix for the 2002 data set was caused by lower delivered costs for natural gas than for coal in some price scenarios and some regions of the country. This finding is still under investigation and we expect that results from the now-completed 2006 data set will help to settle the question. To improve computational tractability with large numbers of scenarios in the stochastic model, we developed a heuristic importance sampling scheme that integrates well with the rolling horizon solution procedure. This development permitted solution of the full monthly model (without quarterly aggregation previously introduced) and confirmed the qualitative comparison between solutions of the stochastic and deterministic versions of the problem.

References for Section A.2

[A2-1] S. Ryan and Y. Wang, "Efficient methods for solving a large-scale multistage stochastic program," INFORMS Annual Meeting, Seattle, November 2007
[A2-2] Y. Wang and S. Ryan (2007). Effects of uncertain fuel costs on optimal energy flows in U.S. Submitted to *Computers & Operations Research*, under revision.

B. Agent-Based Behavioral Model:

In April 2003 the U.S. Federal Energy Regulatory Commission (FERC) proposed a wholesale power market design for U.S. energy markets featuring the ISO/RTO management of a two-settlement system (real-time and day-ahead markets) with locational marginal pricing to handle congestion on the transmission grid. Over 50% of generation capacity in the U.S. today is now operating under some variant on this design.

The primary objective of this part of our NSF project has been to develop AMES, an agent-based wholesale power market test bed capturing core aspects of FERC's market design, as a commercial overlay for the NEES structural network model. The first version of AMES (V1.31) was released as open-source software at the IEEE PES General Meeting in June 2007. A more powerful version of AMES (V2.0) was released online as open-source software on July 10, 2008, and was formally presented at the IEEE PES General Meeting in July 2008.

This work, supervised by Dr. Tesfatsion, is published in the references [B-1]-[B-9]. There have also been two software releases corresponding to this work [B-10, B-11].

B.1 Key Features

As indicated in Fig. B.1, AMES models wholesale power market traders as learning agents capable of autonomous goal-seeking behaviors and strategic response to the incentives intentionally or unintentionally built into FERC's market design. The wholesale power market operates over a transmission grid subject to congestion effects. The ISO handles congestion by the inclusion of congestion cost components in locational marginal prices derived from DC optimal power flow solutions.

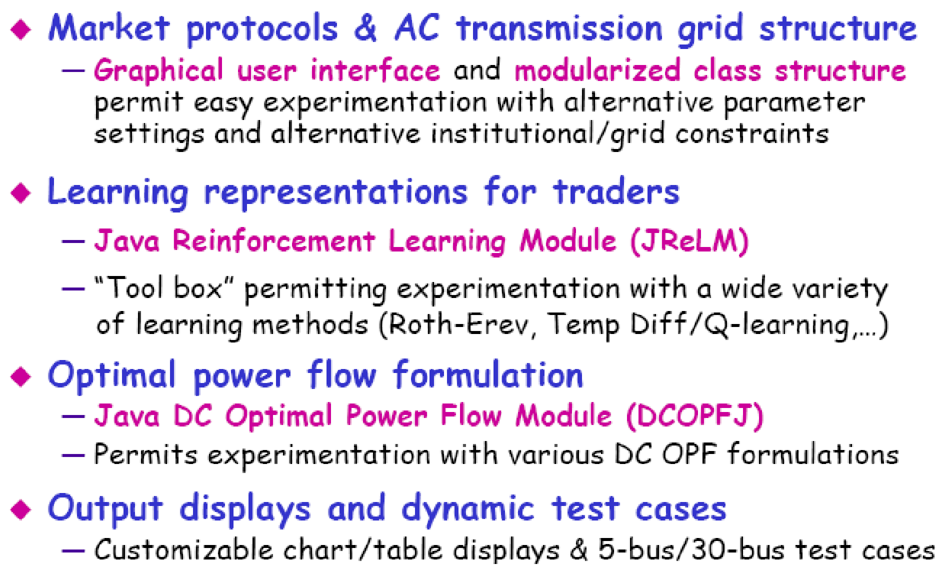

Fig. B.1: AMES Modular and Extensible Architecture

The activities of the ISO on a typical day D are schematically depicted in Fig. B.2. The indicated timing is adopted from the MISO.

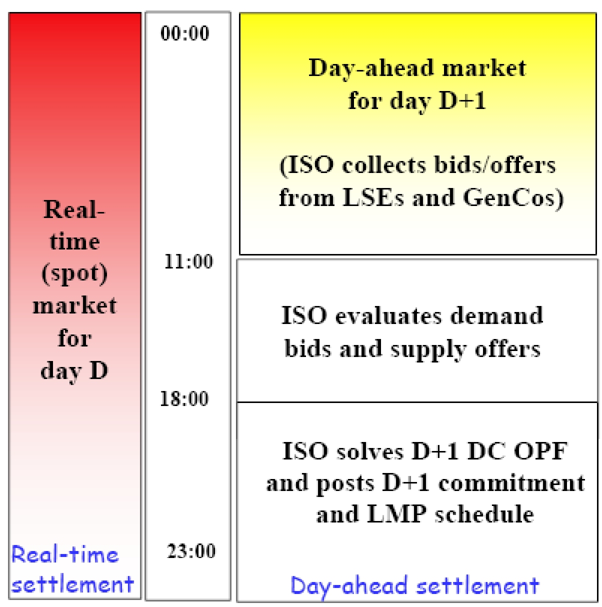

Fig. B.2: AMES ISO activities during a typical day D

As depicted in Fig. B.3, AMES is currently implemented by means of three main Java modules: a learning module for traders; a DC-OPF module for the determination of commitment/LMP solutions for the day-ahead (and real-time) markets; and a graphical user interface (GUI) with separate screens for carrying out many important user functions (e.g., case study creation and modification, customizable output table and chart displays, and setting of stopping rules and other simulation control aspects).

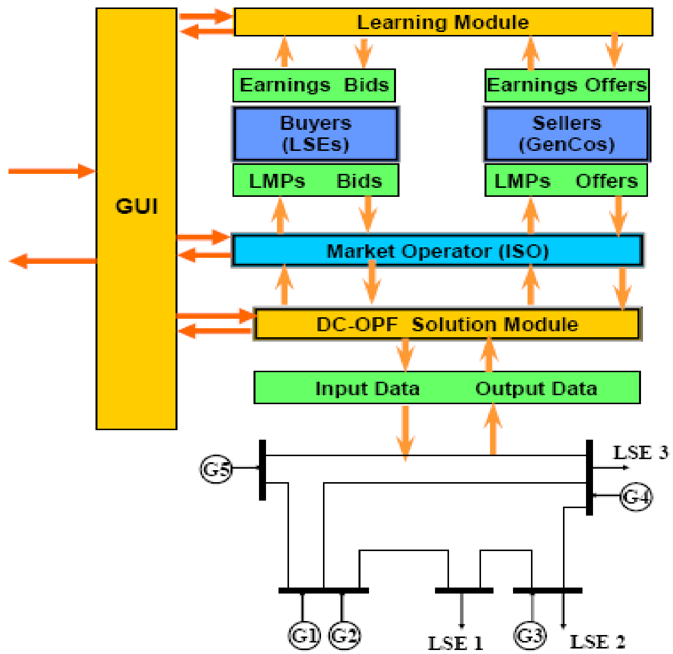

Fig. B.3: Depiction of AMES dynamics on a typical day D in the absence of shocks (i.e., when day-ahead market contracts are fulfilled as planned)

B.2 Key Findings

The following findings are based on extensive experiments with a dynamic 5-bus test case, an extension of a static 5-bus example now routinely used in ISO-NE and PJM training manuals. The test case is shown in Fig. B.4.

- Using only simple stochastic reinforcement learning, generation companies (GenCos) quickly learn to tacitly collude on reported marginal cost functions (supply offers) for the day-ahead market that are higher than their true marginal cost functions, resulting in higher locational marginal prices (LMPs).
- This result holds for all tested levels of price sensitivity for the bid-in demand by load-serving entities (LSEs), ranging from 100% fixed demand (no price sensitivity) to 100% price sensitivity.
- However, LMPs are substantially higher the greater the percentage of fixed to price-sensitive demand.
- Supply-offer price caps, i.e., upper bounds imposed on the GenCos' reported marginal cost functions (supply offers), can decrease average LMP.
- However, the imposition of strongly binding supply-offer price caps can lead to increased LMP spiking and volatility around peak demand hours.

These key findings are more fully explained and illustrated in the following summary paragraphs.

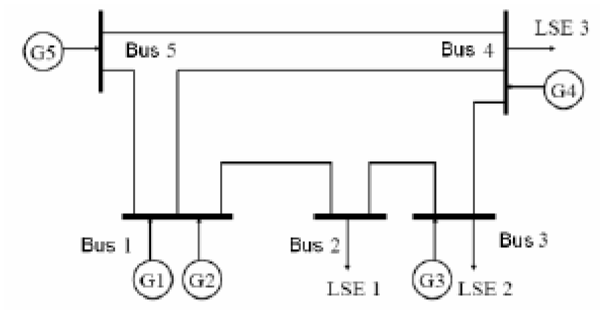

Fig. B.4: Transmission Grid for the Dynamic 5-Bus Test Case

One key treatment factor considered in the experiments reported below is the ratio R of maximum potential price-sensitive demand to maximum potential total demand. The construction of the R ratio is illustrated in Fig. B.5.

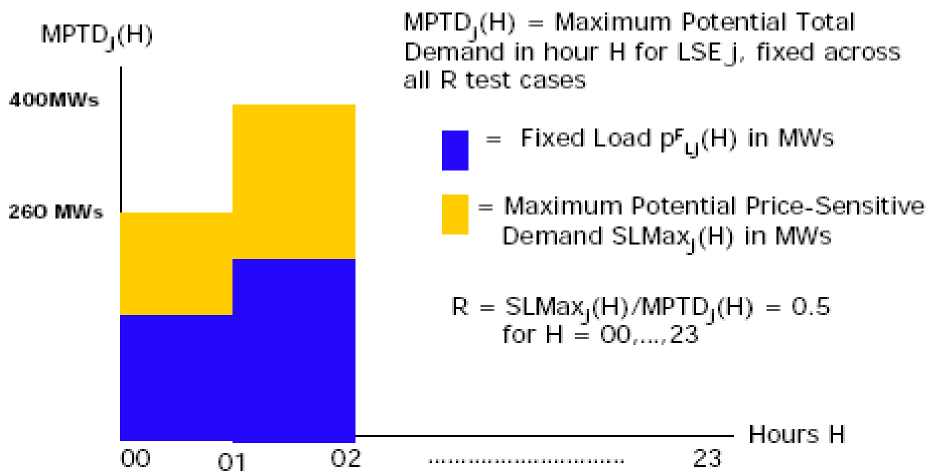

Fig. B. 5: Construction of R ratio for measuring relative demand-bid price sensitivity illustrated for the special case R=0.5

A second key treatment factor is a supply-offer price cap. This price cap is an upper bound imposed on the marginal cost functions that GenCos can report to the ISO for the day-ahead market as part of their supply offers; it is not a cap on LMPs per se.

Table B.1 reports experimental findings for average outcomes under alternative settings for the R ratio (relative demand-bid price sensitivity) in the absence of a supply-offer price cap and with no GenCo learning. Table B.2 reports results for a repeat of these R experiments for the case in which GenCos learn to report strategic supply offers to the ISO over time.

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

Table B.1: Average effects of R changes with no supply-offer price cap and no GenCo learning as R varies from 0.0 (no price-sensitive demand) to R=1.0 (100% price-sensitive demand)

As seen in Table B.1, in the absence of GenCo learning an incremental increase in R starting from the benchmark case R=0.0 (no price-sensitive demand) and terminating at R=1.0 (100% price-sensitive demand) has the usual intuitively-expected effects. Average LMP, average total demand, average operating costs, and the average Lerner Index (LI) measurement for market power all monotonically decline with increases in R. Indeed, except for the presence of binding operating-capacity constraints on GenCos for low R ratio values (i.e., when average total demand is relatively high) and congestion on branch 1-2 leading to LMP separation and out-of-merit-order commitment, all of the average LI outcomes reported in Table B.1 would be zero. GenCos have no learning capabilities and are reporting their true cost and capacity conditions to the ISO each day; they are not making any deliberate efforts to exercise market power.

Comparing the no-learning Table B.1 results to the results with GenCo learning reported in Table B.2, it is seen that GenCo learning has strong effects on average outcomes. With GenCo learning, average LMP, average operating costs, and average LI are all dramatically higher for every level of R even though average total demand is lower. The reason is that the profit-seeking GenCos quickly learn to tacitly collude on higher-than-true reported marginal costs even when demand bids are fully price sensitive (R=1.0) and GenCos are competing for limited demand.

R	Avg LMP	Avg Total Demand	Avg Op Cost	Avg LI
0.0	70.10 (3.14)	318.21 (0.00)	9198.63 (125.88)	0.5692 (0.01)
0.1	73.84 (3.24)	286.39 (0.00)	8450.26 (444.20)	0.5755 (0.01)
0.2	81.46 (2.85)	254.57 (0.05)	7629.94 (298.22)	0.5933 (0.01)
0.3	72.67 (3.02)	223.84 (1.14)	5501.09 (228.62)	0.5433 (0.01)
0.4	39.43 (1.16)	198.70 (2.03)	3300.37 (172.36)	0.4341 (0.01)
0.5	35.75 (0.48)	170.75 (2.42)	2717.73 (157.73)	0.4185 (0.01)
0.6	33.52 (0.41)	155.47 (2.86)	2259.65 (135.01)	0.3660 (0.01)
0.7	28.73 (0.60)	145.84 (4.23)	1877.91 (151.64)	0.2815 (0.01)
0.8	26.75 (0.54)	133.99 (4.96)	1627.45 (157.23)	0.2547 (0.01)
0.9	25.09 (0.51)	120.17 (5.43)	1388.31 (132.60)	0.2342 (0.01)
1.0	23.23 (0.48)	108.51 (5.80)	1184.18 (125.88)	0.2078 (0.01)

Table B.2: Average effects of R changes (with standard deviations) with no supply-offer price cap and with GenCo learning

Table B.3 reports average LMP outcomes under four alternative scenarios for PCap, the supply-offer price cap. For the subsequent interpretation of these findings, it is important to recall that PCap is a price cap on GenCo-reported marginal costs and *not* on LMPs per se. LMPs can separate from *all* GenCo-reported marginal costs in the presence of binding GenCo operating constraints and branch constraints, thus PCap is not necessarily an upper bound on LMPs.

	No PCap	PCap=120	PCap=100	PCap=80
Avg LMP with No GenCo Learning	25.18	25.18	25.18	25.18
Avg LMP with GenCo Learning	70.10 (3.14)	65.72 (4.01)	58.00 (1.51)	54.96 (2.41)

Table B.3: Average LMP response (with standard deviations) to changes in PCap, the supply-offer price cap, for R=0.0 (no price-sensitive demand)

As intuitively expected, with GenCo learning, average LMP in TableB.3 monotonically decreases as PCap is decreased in increments from an effectively infinite value (No Price Cap) to a low value ($80/MWh). Due to learning and network effects, however, the relationship between PCap and LMP outcomes is more complicated than indicated by this average LMP effect.

In particular, note in Table B.3 that average LMP with no price cap is $70.10/MWh whereas average LMP for PCap=$120/MWh is only $65.72/MWh. This finding indicates that the high PCap level $120/MWh is binding on the GenCos' reported marginal costs even though this PCap level is substantially higher than the resulting value $65.72/MWh for average LMP. A similar comment holds for the remaining two PCap levels.

The explanation for this finding is that the distribution of LMPs across the 24 hours of a day can exhibit substantial fluctuations that are obscured when only daily average LMP outcomes are considered. In particular, the maximum LMP value attained during peak demand hours can be substantially higher than average LMP calculated across all 24 hours. Thus, the imposition of a price cap can be a binding constraint on GenCo-reported marginal costs during peak demand hours even if not in other hours. Since GenCos are only permitted to report one supply offer per day, a binding constraint on reported marginal costs during peak demand hours translates into a binding supply-offer constraint for every hour.

Finally, as shown in Figs. B.6 and B.7 for the tested scenario with no demand-bid price sensitivity (R=0.0) and with GenCo learning, the introduction of a binding PCap level can in some cases induce more fluctuations in hourly LMPs while in other cases fluctuations are dampened. In particular, the introduction of the strongly binding PCap level $80/MWh increases both volatility and spiking whereas the introduction of the more moderately binding PCap levels $120/MWh and $100/MWh have the opposite effect**.**

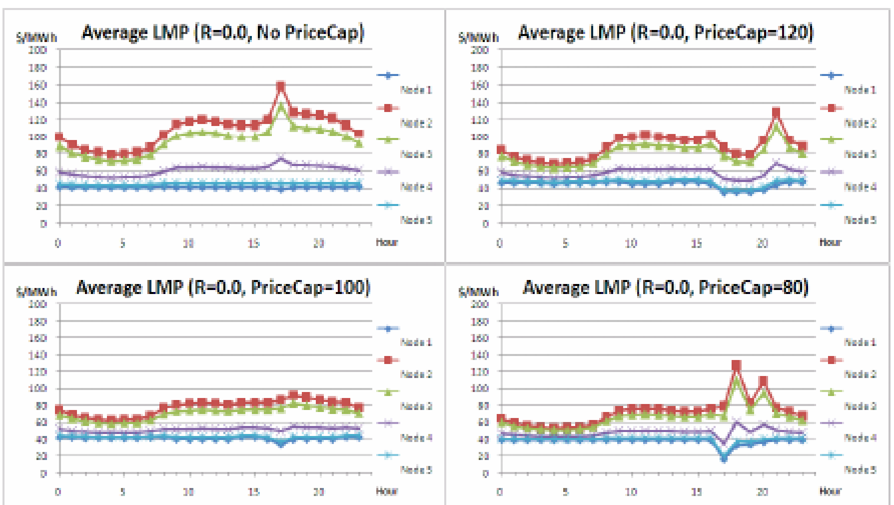

Fig. B.6: Average hourly LMP response to changes in PCap, the supply-offer price cap, with R=0.0 (no price-sensitive demand) and with GenCo learning

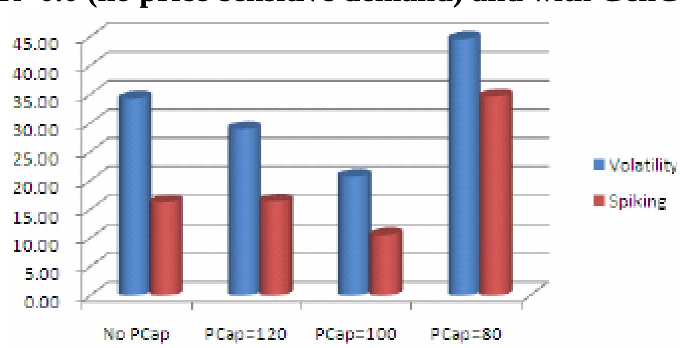

Fig. B.7: Average LMP volatility and spiking under varied supply-offer price caps with R=0.0 (no price-sensitive demand) and with GenCo learning

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[B-9] S. Widergren, J. Sun, and L. Tesfatsion (2006), "Market Design Test Environments," *Proceedings*, IEEE PES GM, Montreal, June.

[B-10] H. Li, J. Sun, and L. Tesfatsion, "The AMES Wholesale Power Market Test Bed (Java): A Free Open-Source Computational Laboratory for the Agent-Based Modeling of Electricity Systems." Version 1.31, released at the IEEE PES GM, June 2007, and Version 2.01 released at the IEEE PES GM, July 20-24, 2008. For extensive materials related to AMES, visit the AMES homepage at http://www.econ.iastate.edu/tesfatsi/AMESMarketHome.htm

[B-11] J. Sun and L. Tesfatsion, "DCOPFJ (Java): A Free Open-Source Solver for Bid/Offer-Based DC Optimal Power Flow Problems," Versions 1.0 and 2.0 released at the IEEE Power and Energy General Meeting, June 2007. For extensive materials related to DCOPFJ, visit: http://www.econ.iastate.edu/tesfatsi/DCOPFJHome.htm

C. Model integration:

In collaboration with University of Auckland researchers, we investigated equilibrium models for an electricity market broadly modeled after the FERC proposed Wholesale Power Market Platform where the electricity generators are supplied by a minimum cost fuel network as in the bulk energy transportation model. We compared models having different assumptions about the bounded rationality of generators for (i) existence and uniqueness of equilibria, (ii) computational tractability, (iii) electricity generation, transmission, LMPs and welfare measures against those of this project's agent-based behavioral model, and (iv) their predictions of the effects of infrastructure improvements on social welfare measures. This work, supervised by Dr. Ryan, is described below and will be published in [C1].

We selected an electricity market equilibrium model to achieve an appropriate trade-off between realism and tractability given the size and complexity of the fuel supply network. We adapted the same five-bus system on which the behavioral (learning agent) model has been tested extensively and fit parameters for a fuel supply network to match the assumed marginal costs. The equilibria were qualitatively similar to the results of the agent simulation in that congestion occurred consistently on the same line and spatial/temporal patterns in LMPs were similar. These equilibria were more competitive, resulting in higher consumer surpluses and lower producer surpluses than in the learning agent model, though the total social welfare was roughly the same. The next objective was to investigate where and how improvements in infrastructure (fuel transportation or electricity transmission) would affect social welfare. Some anomalous behavior has prompted ongoing investigation using 2- and 3-node example networks. We have found instances where (a) increasing the capacity of a low-cost fuel line increases total welfare under a bounded rationality assumption but decreases it if the generators are assumed fully rational; (b) increasing the capacity of a low-cost fuel arc decreases total welfare under bounded rationality but there are infinitely many equilibria under full rationality; or (c) increasing electricity transmission capacity decreases total welfare under bounded rationality but increases it under full rationality. The exact role that the fuel supply network-induced cost structure plays in producing these effects is still under investigation.

<u>References for Section C</u>:

[C1] S. Ryan, A. Downward, A. Philpott and G. Zakeri (2008). Effects of infrastructure improvements on total welfare in a congested electricity network. In preparation.

<u>D. Impediments to transmission line investment</u>:

One viable approach to relieving electric transmission congestion as identified by the National Electric Transmission Congestion Study of 2006 is the construction of additional high voltage transmission lines within designated regions of the United States. Unfortunately, public support for transmission capacity expansion is not guaranteed and, to some extent, affects support for expansion by critical state-level public and private entities. The sociological component will assess public opinions about the routing, construction, and operation of additional high voltage transmission lines within selected areas of the Department of Energy and Midwest Independent Service Operator Transmission Expansion Plans. The survey will examine public opinions within Minnesota, Ohio, Virginia, Maryland, Pennsylvania, New York, Iowa, South Dakota, and Wisconsin. This work is supervised by Dr. Sapp.