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Effects of Price-Responsive Residential Demand on Retail and Wholesale Power Market Operations

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***Abstract*—This paper describes a computational platform for studying the effects of price-responsive residential demand for air-conditioning (A/C) on integrated retail and wholesale power market operations. The physical operations of the A/C system are represented by means of the physics-based equivalent thermal parameter model. Residential A/C energy usage levels are determined by means of a stochastic dynamic-programming optimization in which the daily comfort attained by the resident is optimally traded off against his daily energy costs, conditional on retail energy prices, environmental conditions, and A/C operational constraints. An example is provided to illustrate the dynamic feedback loop connecting residential A/C load, the energy prices determined at wholesale conditional on A/C load, and the retail energy prices offered to residential A/C consumers by wholesale energy buyers.**

***Index Terms*—Air conditioning, demand response, dynamic programming, electricity market, smart grid.**

I. Introduction

TRADITIONALLY in the United States the generation, transmission, and distribution of electric power was monopolistically controlled by vertically integrated utilities with retail load obligations serviced under retail rates fixed by state and/or local agencies. As a result of the restructuring movement over the past fifteen years, however, over half of all generating units are now operating within ISO/RTO-managed energy regions in which generation is required to be unbundled from transmission operations. Moreover, under recent efforts to incorporate smart-grid features, the power industry is increasingly experimenting with means for permitting more active participation by retail consumers in power industry operations.

One advance along these lines has been the development of advanced metering infrastructure whose future implementations might be able to report dynamic price signals to retail consumers reflecting actual energy costs. These costs in general will be related to the charges paid at wholesale by load-serving entities (LSEs). This sets up an interesting feedback dynamic between retail and wholesale levels of operation: Retail loads enter into the determination of wholesale energy prices, which in turn affect the retail prices set by LSEs through retail dynamic-price contracts.

This paper describes a computational platform to investigate the effects on retail and wholesale power system operations when the air-conditioning (A/C) systems of household residents are responsive to price. Residential A/C constitutes a substantial component of load, especially during hot days. A critical requirement for this analysis is the representation of the load profiles arising at the wholesale level from price-responsive retail demands.

Several attempts have been made in the past to achieve a high-fidelity modeling of load. For example, Kosterev et al. [1] discuss the latest advances in load modeling for the study of power systems in the Western Electricity Coordinating Council (WECC) region. Also, Schneider and Fuller [2] provide a detailed discussion of end-use load modeling for distribution analysis. In particular, note that loads with thermal cycles can utilize thermal storage to shift loads to periods with lower prices. Heating, Ventilation, and Air-Conditioning (HVAC) systems constitute a major portion of the load having thermal cycles. The power consumption of an HVAC system is directly dependent on its set-point. Hence, a simple logic such as increasing (decreasing) the set-point of an HVAC system in the cooling mode during high (low) prices can be used to achieve a price-responsive HVAC controller. Schneider et al. [3] use the set-point adjustment method to study the effects of price-sensitive HVAC demand on the operations of a distribution feeder, where retail prices are exogenous values set by the modelers. Zhou et al. [4] extend these studies by using real-time price realizations to test the effects of price-sensitive HVAC demand, whereas Fuller et al. [5] use a price realization from a double-auction capacity management market.

Although the simple set-point adjustment method considered in these earlier studies permits the straightforward derivation of a price-sensitive load profile across residents, it does not take into account in any carefully considered manner the preferred comfort-cost trade-offs of each resident. Moreover, the dynamic circular flow connecting retail loads, wholesale energy prices, and retail energy prices is not fully modeled.

Building on prior work by the authors and their collaborators [6], this study utilizes a computational model of a household with an intelligent A/C system that responds not only to price signals but also to the household resident's preferred comfort-cost tradeoffs. The physical operations of the A/C system are represented by means of the physics-based Equivalent Thermal Parameter (ETP) model [7], [8]. The resident's A/C energy usages are then determined by means of a stochastic dynamic-programming optimization in which the daily comfort attained by the resident is optimally traded off

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against his daily energy costs. This optimization is conditional on resident attributes (e.g., preferences), structural attributes (e.g., house insulation), environmental attributes (e.g., outside temperature), A/C operational attributes, and retail energy prices.

Given this formulation for a single household, a collection of households is then computationally modeled, each with an intelligent A/C system but with differing residential preferences and structural attributes. The price-sensitive retail loads arising from this diverse collection of households affect the determination of wholesale energy prices and hence the costs paid by LSEs for their wholesale energy purchases. These LSE costs in turn affect the retail energy prices that the LSEs charge their retail household customers. The overall effects of this feedback loop on system performance are then studied by means of controlled computational experiments.

The remainder of this paper is organized as follows. Section II describes the computational platform. Section III presents a five-bus test case, and Section IV explains the methodology used to represent aggregate retail load at any load bus by means of distribution feeder data. The general simulation methodology used to implement an integrated modeling of retail and wholesale power system operations with price-responsive A/C residential demands is presented in Section V and illustrated for the five bus test case in Section VI. Concluding remarks are given in Section VII.

II. Integrated Retail and Wholesale Test Bed

This study makes use of an agent-based platform to model retail and wholesale power markets operating over transmission and distribution networks. This platform, referred to as the Integrated Retail and Wholesale (IRW) Power System Test Bed [9], makes use of an extended version[1] of AMES [10] to simulate a wholesale power market adhering to standard market practices, and GridLAB-D to model end-use loads.

This extended version of AMES (*A*gent-based *M*odeling of *E*lectrical *S*ystems) is a modular agent-based computational platform for the study of wholesale power systems that has been developed in Java by a group of researchers at Iowa State University. It is based on the actual design of U.S. restructured wholesale power markets adhering to standards set by the U.S. Federal Energy Regulatory Commission. The agents in AMES include an Independent System Operator (ISO), Generating Companies (GenCos), and Load Serving Entities (LSEs). The GenCos and the LSEs participate in a two-settlement system consisting of a day-ahead and a real-time market operated and settled by the ISO. Transmission grid congestion is managed by Locational Marginal Prices (LMPs).

GridLAB-D [11] is a modular agent-based energy distribution platform developed by DOE researchers at Pacific Northwest National Laboratory (PNNL) that provides detailed models of loads arising from residential, industrial and commercial retail consumers with a variety of appliances and equipment. The MySQL database server is used to facilitate data storage for analysis and data transfer between the various applications. As will be clarified in later sections, GridLAB-D is used in this study to generate the non-price-responsive load profiles for modeled households.

[1]The released AMES version (V2.05) does not consider discrepancies between cleared loads in the day-ahead market and actual real-time loads. The extended version of AMES has a fully operating two-settlement system (day-ahead and real-time markets operating in tandem) that prices such load discrepancies at real-time market prices, as is standard practice in US restructured electric energy regions.

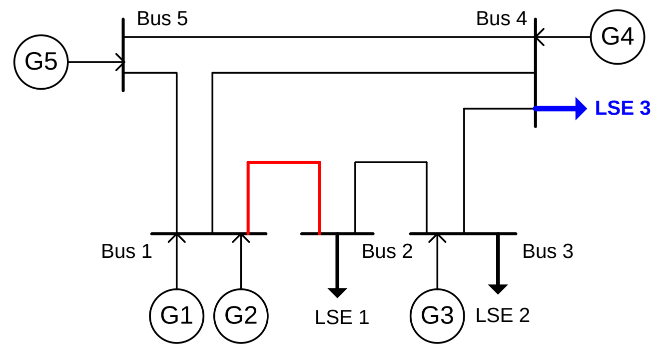

Fig. 1. Power grid for the 5-bus test case.

III. Five-Bus Test Case

For concrete illustration, consider a 5-bus test case with five GenCos, three LSEs, and a high-voltage transmission grid consisting of six lines, as shown in Fig. 1.[2] The power flow limit (250 MW) on the line between buses 1 and 2 typically results in congestion occurring on this line throughout the day.

As explained more carefully in Section IV, the demand at bus 4 (where LSE 3 is located) is extracted from a realistic representation of a distribution system using a GridLAB-D distribution feeder. Demand at all other load buses is modeled by means of the exogenously specified load profiles shown in Fig. 2(c), which have a coincident peak observed at hour 18.

The peak power of the load at buses 2 and 3 is on the order of several hundred MW. On the other hand, the power rating for the distribution feeders modeled in GridLAB-D ranges from 948 KVA to 17 MVA depending on the type of load area (e.g., rural, suburban, heavy urban) and the composition of the load (residential, agricultural, and industrial) [12]. To obtain a load at bus 4 of approximately the same magnitude, the GridLAB-D loads are simply scaled by an appropriate factor.

The marginal cost function for GenCo i is given by

$$\frac{dC(P_{Gi})}{dP_{Gi}} = a_i + 2b_iP_{Gi},\ Cap_i^L \leq P_{Gi} \leq Cap_i^U \qquad (1)$$

for $i = 1, 2, \ldots, 5$. The specific parameter values used in this study for the GenCos' marginal cost functions and their lower/upper generation capacity limits are listed in Table I.

IV. Load Aggregation

A "heavy urban" distribution feeder is selected as the distribution feeder from GridLAB-D to model aggregate load

[2]Apart from the modeling of price-responsive load for LSE 3, explained below, complete input data for the 5-bus test case used in this study are provided in the input data file for the 5-bus test case (with 100% fixed loads) included in the data directory of the AMES(V2.05) download package [10].

TABLE I
PARAMETER VALUES FOR THE GENCOS' MARGINAL COST FUNCTIONS AND LOWER/UPPER GENERATION CAPACITY LIMITS.

GenCo	a $/(MW)	b $/(MW^2)	Cap^L MW	Cap^U MW
1	14	0.005	0	110
2	15	0.006	0	100
3	23	0.010	0	520
4	30	0.012	0	200
5	10	0.007	0	600

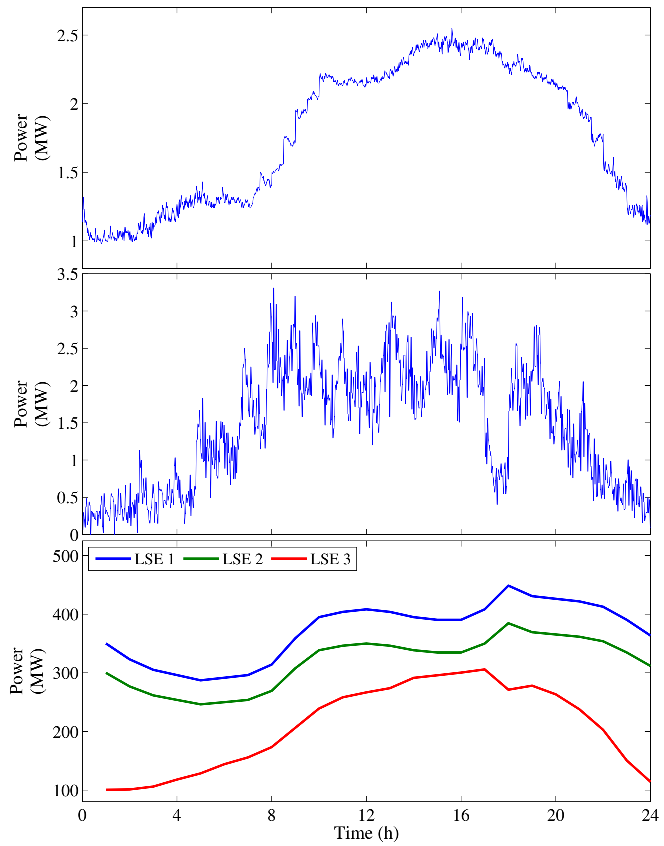

Fig. 2. a) Non-price-responsive load in the distribution feeder; b) Intelligent A/C load in the distribution feeder; c) Daily load profiles for the LSEs, averaged by hour.

at bus 4 of the 5-bus test case. This distribution feeder, labeled as R1-12.47-4 in the taxonomy feeder model [13], represents a heavily populated suburban area mainly composed of single-family houses and heavy commercial loads. There are 38 residential and 12 commercial transformers installed in this feeder, and the peak load is 5.3 MW.

The feeder contains hundreds of houses with detailed end-use loads, such as traditional A/C systems, lights, and various types of appliances. For the purposes of this study, the traditional A/C systems are replaced with intelligently controlled A/C systems as modeled in [6]. The feeder load is thus divided into two parts: non price-responsive load obtained by simulating the feeder with all A/C systems in all households turned off; and the intelligently controlled A/C load, which is calculated separately. The non price-responsive load can be simulated off-line in GridLAB-D for the duration of the simulation. This eliminates the need to run GridLAB-D in tandem with AMES. For simplicity, the same load profile is used for each day of the simulation, as shown in Fig. 2(a). This is scaled up to 220 MW peak in order to match the power rating of other buses in AMES.

The distribution feeder comprises 652 households, and a real power system may feed tens of thousands of households in each bus. If the distinct structural attributes (e.g., insulation levels and size dimensions) of each household were to be modeled, the simulation would become computationally intractable. Consequently, the households are divided into ten groups (of 65 households), where each house within a particular group has identical structural attributes.

The thermal dynamics of each house are modeled using the ETP model [7], [8]. More precisely, the ETP model supposes that the dynamics of the inside air temperature T^a and the inside mass temperature T^m at time t are defined by a system of two first-order linear differential equations:

$$\frac{dT^a}{dt} = \frac{1}{C^a}\left[(T^o - T^a)U^a + (T^m - T^a)U^m + \dot{Q} + \dot{Q}^a\right] \tag{2}$$

$$\frac{dT^m}{dt} = \frac{1}{C^m}\left[(T^a - T^m)U^m + \dot{Q}^m\right] , \tag{3}$$

where

$$\dot{Q}^a = f(\dot{Q}^s, \dot{Q}^i) \tag{4}$$

$$\dot{Q}^m = g(\dot{Q}^s, \dot{Q}^i) . \tag{5}$$

In these equations, C^a is the heat capacity (BTU/°F) of the internal air mass, C^m is the heat capacity (BTU/°F) of the internal solid mass, U^a is the thermal conductance (BTU/h/°F) between internal and external air mass defining the thermal envelope of the house and U^m is the thermal conductance (BTU/h/°F) between the internal air mass and the solid mass. T^o is the outside temperature (°F). $\dot{Q}^s$ is the heat flow rate (BTU/h) from the solar radiation, and $\dot{Q}^i$ is the heat flow rate (BTU/h) from internal appliances and occupants.

The term $\dot{Q}$ that appears in (2) is the heat flow rate (BTU/h) from the A/C system to the internal air mass. It is dependent on the A/C rating (BTU/h) and the latent cooling load (i.e., the unwanted moisture that needs to be removed) which depends on the relative humidity. The overall electricity power consumption depends on $\dot{Q}$ and the coefficient of performance COP (unit-free) of the A/C. The structural attributes of the ten groups of households along with their operational attributes are listed in Table II.

The 65 household residents within each particular group are then allowed to have different A/C comfort-cost trade-off preferences as captured by a "marginal utility of income" parameter α [6] varying over eight different possible settings. For simplicity, the residents' temperature "bliss points" are assumed equal. In total, then, the distribution feeder includes $10 \times 8 = 80$ distinct household types differing by structural and/or preference parameter settings. This approach results in a tractable modeling for diverse price-sensitive A/C residential demands.

TABLE II
STRUCTURAL AND OPERATIONAL ATTRIBUTES OF THE TEN GROUPS OF HOUSEHOLDS

Group	C^a	C^m	U^a	U^m	COP	A/C Rating
1	600	4791	180	6167	3.4	30000
2	1283	10348	432	10473	3.1	72000
3	1477	8745	517	11592	3.4	78000
4	414	2724	235	4812	2.5	30000
5	982	5398	439	8663	3.0	72000
6	1113	8542	506	9465	3.3	78000
7	1036	8745	601	8997	2.7	84000
8	710	5046	497	6921	2.7	66000
9	419	2267	542	6617	2.3	78000
10	1236	6662	924	10089	2.7	114000

Fig. 2(b) depicts the aggregated intelligent A/C load of the distribution feeder for an arbitrary day, conditional on environmental conditions and on retail price, shown in Figs. 3 and 4, respectively. Day-ahead forecasts of the environmental conditions are used for scheduling, while the real-time conditions are used to generate the actual load of the intelligent A/C system. The decrease in the intelligent A/C load at hour 18 (see Fig. 2(b)) is due to the peak retail price observed at that hour (based on the demand bids submitted by the LSEs the previous day), which is shown in Fig. 4. The peak power from the intelligent A/C loads is scaled up to 50 MW. This power level for the price-responsive demand constitutes around 20% of the total feeder load. The peak load of the distribution feeder is around 5 MW, which is less than the rating of the feeder (5.3 MW). Fig. 2(c) depicts the total aggregated load at the wholesale level at bus 4 (where LSE 3 is located), averaged over an hour in accordance with standard market practices.

V. SIMULATION METHODOLOGY

The logical flow of a simulation run is depicted in Fig. 5. Each simulation run can be decomposed into two parts, off-line and on-line. The off-line part involves initial configuring for the distribution feeder(s) and for AMES.[3] The on-line part schematically depicts the dynamic operation of the AMES two-settlement system (parallel day-ahead and real-time market clearing).[4]

In the off-line part, the distribution feeder is first selected, and then the structural house parameters required for implementation of the ETP model are then extracted. Next, to obtain a daily non price-responsive load profile at each feeder-extended AMES bus, a simulation is performed on each feeder with all conventional A/C systems turned off for all houses.

As an additional off-line step, AMES has to be initialized on the initial simulation day 1 with "cleared" LSE demand bids for day 2 (i.e., an amount of energy scheduled to be purchased by each LSE for each hour of day 2), together with 24 hourly energy prices (LMPs) for day 2. These LMPs are interpreted

[3]Although in this study the load at only one AMES bus is extracted from the retail power system, the simulation methodology presented in this section assumes a more general case in which multiple AMES buses are potentially extended with loads extracted from retail power systems.

[4]A two-settlement system design for wholesale power system operations has now been adopted in each of the seven U.S. ISO/RTO-managed energy regions: namely, CAISO, ERCOT, ISO-NE, MISO, NYISO, PJM, and SPP.

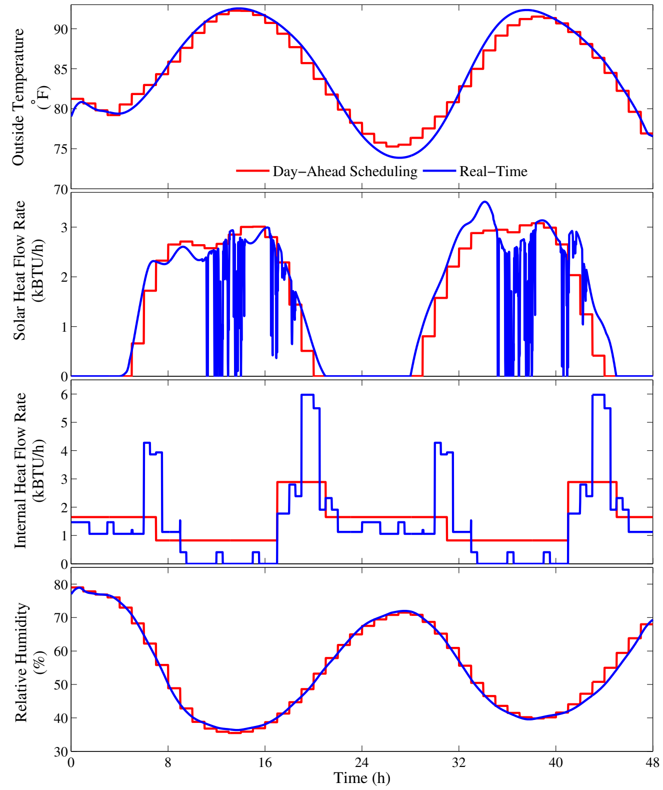

Fig. 3. Variation of environmental parameters for day-ahead scheduling and real-time simulation.

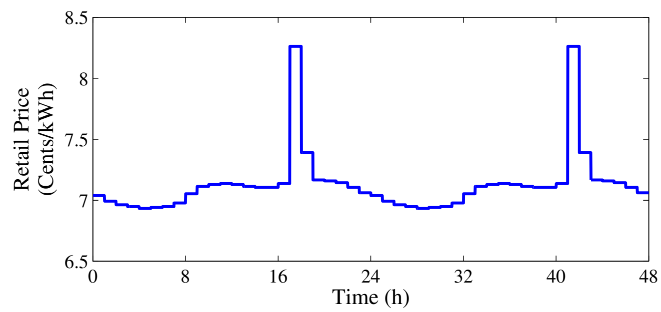

Fig. 4. Retail price variation.

as the (forward) market clearing price solutions determined in the day-ahead market on day 1 (along with cleared energy bid/offer solutions) for each hour of the following day. These LMPs also determine the costs paid by LSEs on day 1 for their cleared demand bids for day 2. The 24 hourly retail energy prices that the LSEs charge to their residential customers during day 2 are determined as a function of these day-1 costs. For example, if an LSE on day 1 pays p \$/kWh for its cleared demand bid for noon on day 2, it might set its retail energy price for noon on day 2 equal to p plus some mark-up amount m to cover billing and other services.

In the on-line part, a Data Management Program (DMP) retrieves from AMES the 24 hourly retail energy prices determined for day 2, using an SQL database server, and passes these retail energy prices to the intelligent A/C system for each house. Each of these intelligent A/C systems then calculates

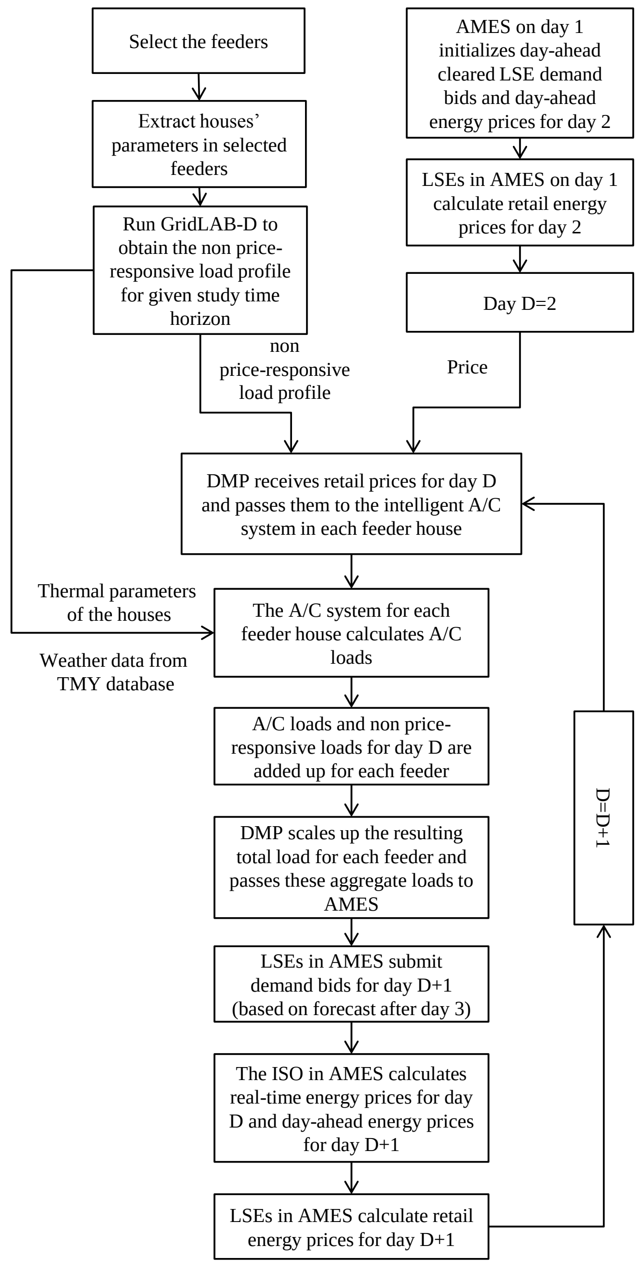

Fig. 5. Flow diagram for a simulation run.

the actual A/C loads for day 2 given these retail energy prices, conditional on its own particular house and resident parameters, home appliance schedule, and the environmental conditions throughout the day.

The DMP then superimposes the total A/C load at each feeder-extended bus with the total non price-responsive load at each feeder-extended bus to form an actual hourly total load (for simplicity, the real-time market is run on an hourly basis in this study) for day 2. These loads are then appropriately scaled up to form the aggregate hourly total load for day 2 at each feeder-extended bus, and passed back to AMES via the SQL database server.

Once AMES receives the aggregate hourly total load for day 2 at each feeder-extended bus along with the loads at all other buses, it can run and clear the real-time market for day 2. This results in real-time LMPs that are used to price any discrepancies between the LSE demand bids for day 2 (contracted in the day-ahead market on day 1) and the realized loads arising from actual household energy usage on day 2.

In parallel with these real-time market operations on day 2, the profit-seeking AMES LSEs submit demand bids into the AMES day-ahead market on the morning of day 2 based on forecasted retail loads for day 3, taking into account the net earnings they obtained from both day-ahead and real-time settlements as a result of their past demand bids.[5] The AMES ISO then clears the day-ahead market on day 2, resulting in 24 hourly energy prices (LMPs) and 24 hourly energy dispatch levels scheduled for the next day 3. These LMPs determine the costs paid by LSEs on day 2 for their cleared hourly energy demand bids for day 3. The 24 hourly retail energy prices that the LSEs charge to their residential customers during day 3 are determined as a function of these day-2 costs.

This sequence of steps is then repeated until a user-specified terminal day.

VI. Illustrative Example

In this section the 5-bus test case described in Section III is used to illustrate the simulation methodology outlined in Section V. Recall that LSEs 1 and 2 located at buses 2 and 3 service fixed load profiles each day. In contrast, LSE 3 at bus 4 services the energy requirements of retail customers whose energy usages are a mixture of non-price-responsive load and intelligent load arising from smart A/C systems.

The 5-bus test case simulation begins on the morning of day 1 with the submission by LSE 3 at bus 4 of an initial demand bid to the ISO for use in the day-ahead market for day 2. This initial demand bid consists of a forecasted 24-hour load profile similar in shape to the 24-hour load profiles submitted as demand bids to the ISO on the morning of day 1 by LSE 1 and LSE 2; see Fig. 2(c). Also on the morning of day 1, the five GenCos submit supply offers[6] to the ISO for use in the day-ahead market on day 2 that consist of their true marginal cost functions and their true capacity limits; see Table I.

The day-ahead market on day 1 is then cleared by the ISO during the afternoon of day 1 using a standard DC optimal power flow formulation, and the resulting hourly day-ahead market LMPs ($/MWh) and dispatch levels (MW) are posted in the evening of day 1. The LSE 3 passes the day-ahead LMPs for bus 4 to its retail customers, amplified by a mark-up factor m = \$50/MWh. The actual hourly loads at bus 4 on day 2 are then determined as explained in Section V.

A new day-ahead market opens on the morning of day 2. Since actual load data have not yet been observed, the demand

[5]AMES permits any decision-making agent to have reinforcement learning capabilities. In general, the profit-seeking AMES LSEs have two learning tasks: namely, to update their daily load forecasts, and to update their daily demand bids based on all relevant past observed data and possibly, also, on strategic trading considerations.

[6]To simplify the illustration, the demand bids (load profiles) submitted by LSE 1 and LSE 2 on day 1, and the supply offers submitted by the five GenCos on day 1, are repeated as their daily demand bids and supply offers throughout the simulation.

TABLE III
SIMULATION RESULTS FOR BUS 4 AT THE PEAK-LOAD HOUR 18

Day	Load^{DA} (MW)	Load^{RT} (MW)	ΔLoad (MW)	LMP^{DA} (\$/MWh)	LMP^{RT} (\$/MWh)	ΔLMP (\$/MWh)	Net Earnings (\$)
1	320.44	N/A	N/A	32.61	N/A	N/A	N/A
2	320.44	237.77	82.67	32.61	30.70	1.91	11730.30
3	237.77	234.06	86.38	30.70	30.61	2.00	11530.42
4	234.06	256.01	-18.24	30.61	31.12	-0.42	12793.03
5	256.01	280.90	-46.84	31.12	31.70	-1.08	13994.32
6	280.90	280.47	-24.45	31.70	31.69	-0.57	14009.48
7	280.47	271.07	9.83	31.69	31.47	0.23	13551.44

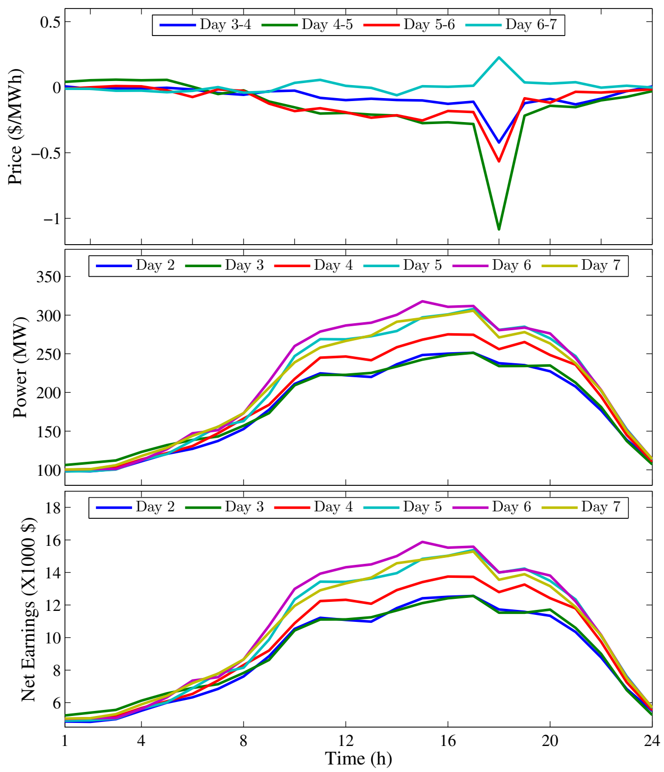

Fig. 6. a) Differences between day-ahead and real-time LMPs; b) The aggregated load profile at bus 4; c) Hourly net earnings of LSE 3 from the two-settlement system.

bids submitted by all three LSEs for this day-ahead market on day 2 are unchanged from day 1. Day-ahead market activities for day 2 then proceed as for day 1. Actual hourly loads are also now realized in the real-time market on day 2.

By the morning of day 3, however, LSE 3 has access to the realized load data for day 2 and can use these data in an attempt to improve its demand bid (load profile forecast) for day 3. For this illustrative example, the following simple forecast methodology is adopted for LSE 3: namely, starting on day 3, the load profile forecast that LSE 3 submits as its demand bid for the day-ahead market is the actual load profile observed for its retail customers on the previous day. Thus, LSE 3 submits a load profile each day that consists of hourly quantities with no explicit dependence on price or environmental conditions; yet these load profiles in fact arise in part from intelligent A/C systems responsive to both price and environmental conditions, hence they vary systematically over time in response to changes in these conditions. On each subsequent simulated day, the LSEs, GenCos, and ISO then proceed through the same progression of activities as on day 3.

Let the demand bid (forecasted load) submitted by LSE 3 in the day-ahead market on day D-1 for bus 4 at hour H on day D be denoted by $\text{Load}^{\text{DA}}_{H,D-1}$, and let the actual aggregate load realized in the real-time market for bus 4 at hour H on day D be denoted by $\text{Load}^{\text{RT}}_{H,D}$. Similarly, let the day-ahead LMP determined on day D-1 for bus 4 at hour H on day D be denoted by $\text{LMP}^{\text{DA}}_{H,D-1}$, and let the real-time LMP determined on day D for bus 4 at hour H on day D be denoted by $\text{LMP}^{\text{RT}}_{H,D}$. The *load forecast error* for bus 4 at hour H on day D is then calculated as

$$\Delta\text{Load}_{H,D} = \text{Load}^{\text{DA}}_{H,D-1} - \text{Load}^{\text{RT}}_{H,D} \,. \tag{6}$$

Similarly, the *price deviation* for bus 4 at hour H on day D is calculated as

$$\Delta\text{LMP}_{H,D} = \text{LMP}^{\text{DA}}_{H,D-1} - \text{LMP}^{\text{RT}}_{H,D} \,. \tag{7}$$

Key results for each of the first seven simulated days are reported in Table III for bus 4 at the peak-load hour 18. For clarity, the subtracted terms used to calculate the load forecast errors (6) and price deviations (7) are highlighted using the same color. As explained above, the LSE demand bids and GenCo supply offers for day 1 are the same as for day 2, hence the day-ahead LMPs for day 1 are the same as for day 2.

Ignoring the first two days used to initialize the simulation, the price deviations (7) are plotted in Fig. 6(a) for D varying from 3 to 7. Since all parameter values remain constant throughout the simulation, along with the daily demand bids of LSEs 1 and 2 and the daily supply offers of the five GenCos, these price deviations are entirely due to LSE 3's load forecast errors. These load forecast errors, in turn, arise due to randomly varying environmental conditions.

The net earnings of LSE 3 at bus 4 for any hour H of any simulated day D = 2,...,7 are determined as follows:

$$\begin{aligned} \text{NetEarnings}(H,D) &= [m + \text{LMP}^{\text{DA}}_{H,D-1}] \cdot \text{Load}^{\text{RT}}_{H,D} \\ &\quad - \text{LMP}^{\text{DA}}_{H,D-1} \cdot \text{Load}^{\text{DA}}_{H,D-1} \\ &\quad + \text{LMP}^{\text{RT}}_{H,D} \cdot [\text{Load}^{\text{DA}}_{H,D-1} - \text{Load}^{\text{RT}}_{H,D}] \,, \end{aligned} \tag{8}$$

where m denotes the mark-up added by LSE 3 to the day-ahead LMP. Collecting terms, (8) can equivalently be expressed as

$$\text{NetEarnings}(H,D) = m \cdot \text{Load}^{\text{RT}}_{H,D} + [\text{LMP}^{\text{DA}}_{H,D-1} - \text{LMP}^{\text{RT}}_{H,D}] \cdot [\text{Load}^{\text{RT}}_{H,D} - \text{Load}^{\text{DA}}_{H,D-1}]\,, \quad (9)$$

or, in more compact form, as

$$\text{NetEarnings}(H,D) = m \cdot \text{Load}^{\text{RT}}_{H,D} - \Delta\text{LMP}_{H,D} \cdot \Delta\text{Load}_{H,D}\,. \quad (10)$$

All else equal, $\text{LMP}^{\text{RT}}_{H,D}$ will tend to move in the same direction as $\text{Load}^{\text{RT}}_{H,D}$. This follows because the real-time aggregate supply curve for hour H of day D is upward sloping, and an increase in $\text{Load}^{\text{RT}}_{H,D}$ results in a rightward shift in the (vertical) real-time aggregate demand curve for hour H of day D. The second term on the right-hand-side of the equality in (9) will thus tend to be negative unless LSE 3's day-ahead hourly load forecast, $\text{Load}^{DA}_{H,D-1}$, is a perfect forecast of its real-time hourly aggregate load, $\text{Load}^{RT}_{H,D}$. Indeed, this is a deliberate design feature of the two-settlement system to encourage accurate LSE load forecasting. Notice, however, that LSE 3 can still earn a positive profit if it is able to set the mark-up m sufficiently high.

The aggregate load profile at bus 4 for each of the simulated days 2 through 7 is shown in Fig. 6(b). LSE 3's corresponding hourly net earnings (10) are plotted in Fig. 6(c). Comparing Fig. 6(b) with Fig. 6(c), it is seen that LSE 3's hourly net earnings are strongly positively correlated with hourly real-time aggregate loads. The explanation for this correlation is that, for the simulation at hand, the load forecast errors (6) and price deviations (7) are very small compared to LSE 3's mark-up earnings $m \cdot [\text{Load}^{\text{RT}}_{H,D}]$ in (10). Hence, LSE 3's net earnings for each hour of day D are approximately determined by its mark-up earnings for this hour.

VII. Conclusion

Given the increased penetration of price-responsive demand envisioned under smart grid initiatives, it is critically important to investigate the effects of this penetration on system operations at both retail and wholesale levels. Price-responsive retail energy demand affects wholesale load and hence wholesale energy prices, which in turn affect the energy prices set by wholesale energy buyers for their retail energy customers.

The primary purpose of the present study is to demonstrate, through concrete illustration, that computational platforms can be developed that permit the systematic study of integrated retail and wholesale power system operations with price-responsive demand. The platform reported in this study is still in a preliminary stage of development, and many possible improvements are under investigation.

For example, one major improvement would be to decrease the computation time needed to simulate the retail-wholesale feedbacks arising from price-responsive retail demand. A resort to parallel computing or supercomputing could speed up the process. The aggregation of the load is also at a very crude modeling stage. The simultaneous simulation of multiple distribution feeders would eliminate the need to scale up the retail load and would permit temporal and spatial load diversity to be captured with greater empirical verisimilitude. In addition, appropriate load forecasting methods for LSEs servicing price-responsive retail demand need to be investigated. The ability of LSEs to use mark-ups over wholesale energy prices also needs to be more carefully examined. Higher mark-ups could lead to higher net earnings in the short-run, but could also ultimately result in lower net earnings if retail customers are able to vote with their feet to patronize lower-priced rival retailers. These and other important issues are subjects of ongoing and future research.

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