The AMES Wholesale Power Market Test Bed as a Stochastic Dynamic State-Space Game

Leigh Tesfatsion*
Professor of Economics
Courtesy Professor of Mathematics
Iowa State University, Ames, Iowa 50011-1070
https://www2.econ.iastate.edu/tesfatsi/
tesfatsi@iastate.edu

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Abstract: The AMES Wholesale Power Market Test Bed is an agent-based computational laboratory designed for the systematic experimental study of restructured wholesale power markets. These notes show how AMES can be recast in more standard state-space equation form. The result is a highly nonlinear and highly coupled system of first-order stochastic difference equations. The AMES state-space equation representation is used to explain how AMES constitutes an open-ended dynamic game among multiple strategically-learning players. It is also used to explain how AMES permits the development and experimental study of a wide variety of test cases.

The AMES Wholesale Power Market Test Bed has been developed by a group of researchers at Iowa State University to facilitate the systematic experimental study of restructured wholesale power markets. The release of AMES(V1.31) was announced at the IEEE Power and Energy Systems General Meeting in June 2007, and the release of AMES(V2.01) was announced at the IEEE Power and Energy Systems General Meeting in July 2008. AMES is an acronym for *A*gent-based *M*odeling of *E*lectricity *S*ystems.

AMES is "agent based" in the sense that it is a computationally constructed virtual world comprising multiple agents (encapsulated software programs) whose various interactions drive all world events over time. Here "agents" must be broadly interpreted to include structural entities (e.g., transmission grids), institutional entities (e.g., markets), non-cognitive biological entities (e.g., switchgrass crops), and cognitive entities (e.g., energy traders and market operators).[1]

As is true for any agent-based model, AMES is most naturally explained in terms of verbal descriptions, diagrams, and pseudo-code expressing the logical flow of agent processes and interactions over time, as an accompaniment to the actual source code. Detailed descriptions of AMES taking these forms can be found in [4, 5, 6], and the source code for the latest AMES version release can be found at the AMES home page [7].

In contrast, models within economics and power systems are typically represented as systems of equations. The question then arises whether AMES can be represented as a system of equations. Moreover, if so, what use can be made of this representation?

The purpose of these notes is three-fold. First, I will demonstrate how AMES can be recast in more standard state-space equation form. The result is a highly nonlinear and highly coupled system of first-order stochastic difference equations. Second, I will use the AMES state-space equation

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[1] See [1] for extensive introductory resources on agent-based computational modeling, including tutorials, readings, software, and websites. Comprehensive surveys of agent-based research in many different economic application areas can be found in [2]; agent-based research specifically focused on electricity markets is highlighted at [3].

representation to explain how AMES constitutes an open-ended dynamic *game* among multiple strategically-learning players. Third, I will use the AMES state-space equation representation to explain how AMES permits the development of a wide variety of test cases suitable for research, teaching, and training purposes.

Many extensions are planned for future versions of AMES. For example, a real-time market paralleling the day-ahead market will be incorporated to implement a fully active two-settlement system, and a Financial Transmission Rights (FTR) market will be incorporated to permit hedging of congestion and price volatility in the day-ahead market. However, these extensions should not substantially change the general state-space equation representation determined below specifically for AMES(V2.01).

1 Representation of the System State Vector

Collection of Agent Types

Structural Agents:

AMES(V2.01) has S=2 structural agents [the world (W) and the transmission grid (TG)]

Institutional Agents:

AMES(V2.01) has H = 1 institutional agents [a day-ahead market (M)].

Cognitive Agents:

AMES(V2.01) has C = [1 + J + I] cognitive agents, as follows: 1 market operator (referred to as the ISO=Independent System Operation); J buyer traders (referred to as LSEs=Load-Serving Entities); and I seller traders (referred to as GenCos=Generation Companies).

Agents in Total:

The total number of agents in AMES(V2.01) is A = [S + H + C].

Agent Characterizations

Each agent a = 1,...,A is an encapsulated software program characterized by its internal methods (functions, routines, processes, procedures,...) and internal data (parameter values, attributes, stored information,...). The methods and data for the AMES World, the AMES Transmission Grid, the AMES Day-Ahead Market, the AMES ISO, and a typical AMES LSE and AME GenCo are schematically depicted in Figures 1 through 6.

As seen in Figure 1, the World agent manages each AMES simulation run. For example, it implements the user-specified simulation stopping rule(s), and it collects and displays data in the graphical user interface in accordance with user specifications. The Transmission Grid agent depicted in Figure 2 and the Day-Ahead Market agent depicted in Figure 3 illustrate how non-cognitive agents in AMES encapsulate methods and data that permit interactions over time with the cognitive agents (i.e., the GenCos, LSEs, and ISO).

As seen in Figures 4 through 6, the GenCos in AMES(V2.01) have relatively more cognitive capabilities and autonomy than the LSEs and ISO in that they have learning methods permitting them to adaptively choose their actions on the basis of their private data. Note, also, that GenCo private data can include accumulated historical data (as is true for other agent types as well).

The Time Frame

Time Indicator: T=(H,D), where H = 00,01,...,23 and D = 1, 2, ...,DMax

Divide time into 24-hour days by defining

Day 1 $\equiv$ {(00,1),(01,1),...,(23,1)},
Day 2 $\equiv$ {(00,2),(01,2),...,(23,2)},
$\vdots$
Day Dmax $\equiv$ {(00,DMax),(01,DMax),...,(23,DMax)}

Then the system runs for days D = 1,...,DMax.

The System State Vector

Let $\mathbf{x}_a$(D) denote the collection of all internal methods and internal data characterizing agent a at the beginning of day D. The *system state vector* at the beginning of each day D=1,...,DMax is then given by

$$\mathbf{x}(D) \ = \ (\mathbf{x}_1(D), \mathbf{x}_2(D), \ldots, \mathbf{x}_A(D)) \tag{1}$$

As indicated in Figures 1 through 6, the private data for the state vector components $\mathbf{x}_a$(D) in (1) can contain adaptively changing agent attributes as well as accumulations of historical data. Consequently, both the contents and the "dimensions" of these components can vary over time.

2 Decision Functions Implemented by the Cognitive Agents

Between hour 00 and hour 11 of each day D, each LSE j chooses a demand bid d_{Lj}(D) as a function

$$d_{Lj}(D) \ = \ d(\mathbf{x}_{Lj}(D), \mathbf{w}_{Lj}(D)) \tag{2}$$

of its own state $\mathbf{x}_{Lj}$(D) and (possibly) a vector $\mathbf{w}_{Lj}$(D) of day-D demand-side disturbances.[2] LSE j reports this demand bid to the ISO at the end of hour 11 of day D.

Also, between hour 00 and 11 of each day D, each GenCo i chooses a supply offer s_{Gi}(D) as a function

$$s_{Gi}(D) \ = \ s(\mathbf{x}_{Gi}(D), \mathbf{w}_{Gi}(D)) \tag{3}$$

of its own state $\mathbf{x}_{Gi}$(D) and (possibly) a vector $\mathbf{w}_{Gi}$(D) of day-D supply-side disturbances.[3] GenCo i reports this supply offer to the ISO by the end of hour 11 of day D.

Let $\mathbf{x}_J$(D) and $\mathbf{w}_J$(D) denote J-dimensional vectors comprising the day-D states and disturbances of the J LSEs, respectively. Also, let $\mathbf{x}_I$(D) and $\mathbf{w}_I$(D) denote I-dimensional vectors comprising the day-D states and disturbances of the I GenCos, respectively. Then the vector

$$\mathbf{z}(D) = (d_{L1}(D), \ldots, d_{LJ}(D), s_{G1}(D), \ldots, s_{GI}(D)) \tag{4}$$

comprising the day-D demand bids (2) and supply offers (3) of the LSEs and GenCos that are reported to the ISO at the end of hour 11 of day D can be expressed as a function

$$\mathbf{z}(D) \ = \ \mathbf{Z}(\mathbf{x}_J(D), \mathbf{x}_I(D), \mathbf{w}_J(D), \mathbf{w}_I(D)) \tag{5}$$

of these states and disturbances.

Between hour 12 and hour 18 of each day D, the ISO determines a 24-hour schedule of cleared real-power bid/offer commitments Pow(D) and locational marginal prices LMP(D)for the day-ahead market for day D+1 as the solution to 24 hourly DC-OPF problems. By construction, this schedule is a function of the current state $\mathbf{x}_{TG}$(D) of the transmission grid, the current state $\mathbf{x}_{DAM}(D)$ of the day-ahead market, the ISO's own current state $\mathbf{x}_{ISO}$(D), the vector $\mathbf{z}$(D) of current LSE demand bids and GenCo supply offers, and (possibly) a vector $\mathbf{w}_S$(D) of day-D system disturbances.[4] Let this function be denoted by

$$(Pow(D), LMP(D)) \ = \ DCOPF(\mathbf{x}_{TG}(D), \mathbf{x}_{DAM}(D), \mathbf{x}_{ISO}(D), \mathbf{z}(D), \mathbf{w}_S(D)) \tag{6}$$

At the beginning of the final hour 23 of each day D, the ISO communicates the commitment/LMP schedule (6) to the LSEs and GenCos and settles all payments. The activities of the ISO during a typical day D are schematically depicted in Figure 7.

[2]AMES(V2.01) has no demand-side disturbances, such as sudden spikes in demand caused by unancipated weather patterns. However, provision for demand-side disturbances is planned for future versions of AMES.

[3]In AMES(V2.01) the day-D "disturbance" $\mathbf{w}_{Gi}$(D) for GenCo i is its random draw of a supply offer in accordance with its latest updated action choice probability distribution, as dictated by its VRE reinforcement learning method. This random draw is implemented by means of a pseudo-random number generator that constitutes part of GenCo i's supply-offer learning method. Currently, however, there are are no external supply-side disturbances such as spikes in fuel costs causing changes in cost functions or forced outages of generation units causing changes in GenCo operating capacities. Provision for external supply-side disturbances is planned for future versions of AMES.

[4]AMES(V2.01) has no system disturbances, such as sudden transmission line outages. However, provision for system disturbances is planned for future versions of AMES.

During the final hour 23 of day D each LSE j estimates – based on its day-D state and disturbance vector – the amount of money it anticipates it would truly be willing to pay for its scheduled demand bid commitments for day D+1. It then calculates its net earnings for day D as the difference between its estimated willingness to pay for its scheduled demand bid commitments on day D+1 and the actual LMP payments it made to the ISO for these commitments at the beginning of hour 23. Thus, the day-D net earnings for LSE j can be expressed as a function

$$NE_{Lj}(D) \ = \ NE(Pow(D), LMP(D), \mathbf{x}_{Lj}(D), \mathbf{w}_{Lj}(D)) \tag{7}$$

of the commitment/LMP schedule (6), LSE j's day-D state vector $\mathbf{x}_{Lj}$(D), and LSE j's day-D disturbance vector $\mathbf{w}_{Lji}$(D).

During the final hour 23 of day D each GenCo i estimates – based on its day-D state and disturbance vector – the total variable costs it will actually have to pay to meet its scheduled supply offer commitments for day D+1. It then calculates its net earnings for day D as the difference between the LMP payments it received from the ISO at the beginning of hour 23 for its scheduled day D+1 supply offer commitments and its estimated total variable cost for these commitments. Thus, the day-D net earnings for GenCo i can be expressed as a function

$$NE_{Gi}(D) \ = \ NE(Pow(D), LMP(D), \mathbf{x}_{Gi}(D), \mathbf{w}_{Gi}(D)) \tag{8}$$

of the commitment/LMP schedule (6), GenCo i's day-D state vector $\mathbf{x}_{Gi}$(D), and GenCo i's day-D disturbance vector $\mathbf{w}_{Gi}$(D).

3 Updating the System State Vector from Day D to D+1

The system state vector $\mathbf{x}$(D) in (1) represents the state of the system at the beginning of day D. This system state vector is updated at the end of the final hour 23 of day D (i.e., at the beginning of the first hour 00 of day D+1).

The components of the system state vector $\mathbf{x}$(D) are the individual states $\mathbf{x}_a$(D) of the A agents at the beginning of day D. Consequently, to construct the update mapping for $\mathbf{x}$(D), it suffices to construct the update mapping for each of its component states $\mathbf{x}_a$(D).

As previously noted, the A agents of AMES(V2.01) consist of the World W, the Transmission Grid TG, the Day-Ahead Market M, the ISO, J LSEs, and I GenCos. The state update mapping for each of these agents will now be derived, using a reversed order to facilitate exposition.

Each GenCo i updates its day-D state $\mathbf{x}_{Gi}(D)$ to include all new information obtained between the start of day D and the end of day D. This new information consists of the day-D disturbance vector $\mathbf{w}_{Gi}$(D), the ISO schedule (6), and the net earnings (8). Checking the functional forms of the latter two pieces of information, it is seen this state updating can be expressed as a mapping having the following form:

$$\mathbf{x}_{Gi}(D+1) \ = \ F_{Gi}(\mathbf{x}(D), \mathbf{w}(D)) \quad , \tag{9}$$

where

$$\mathbf{w}(D) \ = \ (\mathbf{w}_J(D), \mathbf{w}_I(D), \mathbf{w}_S(D)) \tag{10}$$

is the vector consisting of all LSE, GenCo, and system disturbances occuring during day D.

Each LSE j updates its day-D state $\mathbf{x}_{Lj}(D)$ to include all new information obtained between the start of day D and the end of day D. This new information consists of the day-D disturbance vector $\mathbf{w}_{Lj}$(D), the ISO schedule (6), and the net earnings (7). Checking the functional forms of the latter two pieces of information, it is seen this state updating can be expressed as a mapping having the following form:

$$\mathbf{x}_{Lj}(D+1) \ = \ F_{Lj}(\mathbf{x}(D), \mathbf{w}(D)) \tag{11}$$

The ISO updates its day-D state $\mathbf{x}_{ISO}$(D) to include all new information obtained between the start of day D and the end of day D. This new information consists of the day-D system disturbance vector $\mathbf{w}_S$(D), the vector $\mathbf{z}$(D) of LSE and GenCo demand bids and supply offers in (5), and the

ISO schedule (6). Checking the functional forms of the latter two pieces of information, it is seen this state updating can be expressed as a mapping having the following form:

$$\mathbf{x}_{ISO}(D+1) \;=\; F_{ISO}(\mathbf{x}(D), \mathbf{w}(D)) \tag{12}$$

The day-D state $\mathbf{x}_M$(D) of the day-ahead market at the start of day D is updated at the end of day D to the extent that the methods and data comprising this state have been affected by the vector $\mathbf{w}$(D) of day-D disturbances, the vector $\mathbf{z}$(D) of LSE and GenCo demand bids and supply offers in (5), and the ISO schedule (6). Checking the functional forms of the latter two pieces of information, it is seen this state updating can be expressed as a mapping having the following form:

$$\mathbf{x}_{M}(D+1) \;=\; F_{M}(\mathbf{x}(D), \mathbf{w}(D)) \tag{13}$$

The day-D transmission grid state $\mathbf{x}_{TG}$(D) at the start of day D is updated at the end of day D to the extent that the methods and data comprising this state have been affected by the vector $\mathbf{w}$(D) of disturbances occuring during day D. Although in general this updated state will only depend on the past transmission grid state (plus disturbances), it is notationally convenient to express this update mapping as a function of the complete past system state vector as follows:

$$\mathbf{x}_{TG}(D+1) \;=\; F_{TG}(\mathbf{x}(D), \mathbf{w}(D)) \tag{14}$$

Finally, the world state $\mathbf{x}_W$(D) at the start of day D is updated at the end of day D to the extent that the methods and data comprising this state have been affected by the vector $\mathbf{w}$(D) of day-D disturbances, the vector $\mathbf{z}$(D) of LSE and GenCo demand bids and supply offers in (5), and the ISO schedule (6). Checking the functional forms of the latter two pieces of information, it is seen this state updating can be expressed as a mapping having the following form:

$$\mathbf{x}_{W}(D+1) \;=\; F_{W}(\mathbf{x}(D), \mathbf{w}(D)) \tag{15}$$

The state updating functions developed above for each of the A agents in AMES can be compactly expressed in the following *system state update mapping*:

$$\mathbf{x}(D+1) \;=\; \mathbf{F}\left(\mathbf{x}(D), \mathbf{w}(D)\right) \quad , \tag{16}$$

where

$$\begin{aligned}
\mathbf{F}\left(\mathbf{x}(D), \mathbf{w}(D)\right) &= (F_1(\mathbf{x}(D), \mathbf{w}(D)), \ldots, F_A(\mathbf{x}(D), \mathbf{w}(D))) \\
\mathbf{x}(D) &= (\mathbf{x}_1(D), \mathbf{x}_2(D), \ldots, \mathbf{x}_A(D)) \\
\mathbf{w}(D) = (\mathbf{w}_J(D), \mathbf{w}_I(D), \mathbf{w}_S(D)) &= (\mathbf{w}_{L1}(D), \ldots, \mathbf{w}_{LJ}(D), \mathbf{w}_{G1}(D), \ldots, \mathbf{w}_{GI}(D), \mathbf{w}_S(D))
\end{aligned}$$

It follows from (16) that, rendered into dynamic state-space equation form, AMES is a system of stochastic difference equations. The system is "first order" (Markovian) in form, in the sense that the system state vector $\mathbf{x}$(D+1) for day D+1 depends only on the system state vector $\mathbf{x}$(D) for day D together with day-D disturbances.

Nevertheless, it is doubtful indeed whether one would ever want to actually attempt to "solve" AMES by means of (16).[5] First, note there is no way that the components of the system state vector $\mathbf{x}$(D) can be dynamically uncoupled from each other, resulting in A independent stochastic difference equations. In particular, $\mathbf{x}_a$(D+1) can depend on the day-D states $\mathbf{x}_{a'}$(D) and/or day-D disturbance vectors $\mathbf{w}_{a'}$(D) for other agents a'. Moreover, a disturbance can contemporaneously affect many agents at the same time. For example, a system disturbance $\mathbf{w}_S$(D) (e.g., a transmission outage) during day D could affect LSE demand bids and/or GenCo supply offers during day D and so constitute part of the demand-side disturbance vector $\mathbf{w}_J$(D) and/or the supply-side disturbance vector $\mathbf{w}_I$(D).

Consequently, the system (16) of stochastic difference equations is highly nonlinear and highly coupled. Morever, the components $\mathbf{x}_a$(D) of the system state vector $\mathbf{x}$(D) can contain accumulated historical data not representable in the form of fixed-dimension sufficient statistics. In this case these components will not be expressible as elements of some fixed-dimension space.

[5] AMES is in fact "solved" conditional on given user specifications for exogenous variables and functional forms by compiling and running its Java code. See the AMES homepage [7] for details.

4 AMES as an Open-Ended Dynamic Game

A multi-agent system is a *game* if: (i) the payoff for at least one agent a' depends in part on the action(s) of another agent a*; and (ii) agent a' deliberately selects its own actions in an attempt to exploit (or protect itself against) this dependence on a*. In this case agent a' is said to act *strategically* with respect to agent a*.

Perhaps the simplest form of game is a "game against nature" in which an agent is attempting to optimize its action choices within some form of random environment; the latter is then modeled as a second agent who happens to be choosing its actions purely randomly. At the other extreme are systems for which multiple cognitive agents have learning capabilities and all are attempting to optimize their own payoffs over time through appropriate strategic action choices over time.

In AMES(V2.01), only the GenCos have learning capabilities. The specific learning algorithm currently implemented for these GenCos is the VRE reinforcement learning (VRE-RL) algorithm. Given the VRE-RL form of learning, each profit-seeking GenCo learns to choose its supply offers over time on the basis of its own past net earnings. Each GenCo clearly recognizes its net earnings are determined in part by its own supply offers and in part by the DC-OPF method used by the ISO to produce daily commitment/LMP schedules. Consequently, each GenCo clearly recognizes that it is participating in a game with the ISO. The payoffs for each GenCo are its net earnings, whereas the payoffs for the ISO are market performance as measured by total net cost of operations and the reliability of operations over time.

More elaborate forms of games can be obtained by specifying more sophisticated forms of learning for the GenCos (e.g., belief-based), or by permitting the LSEs or ISO to have learning capabilities along with the GenCos. The functional form (5) for the vector of LSE demand bids and GenCo supply offers is very general in terms of the information it permits each of these agents to have about the state of each other agent, and even about the disturbances affecting other agents, prior to its own choice of actions.

As seen from (16), however, even if each AMES cognitive agent in each day D is permitted to have complete information about the day-D states and disturbances of all other agents prior to determining its own day-D actions, AMES in state-space equation form still reduces to a system of first-order stochastic difference equations.

5 AMES Test Case Development

The concept of a "test case" has been used in a variety of ways by different researchers. Here we try to develop the concept in a manner applicable for agent-based test beds as well as more standard equation-based models.

Let a *scenario* be defined as a collection of consistent (i.e., non-contradictory) modeled relationships. Let *input data* for a scenario be defined as specific values and forms for all of the scenario's variables and functions that are *exogenous*, i.e., determined outside of the scenario. The variables and functions of a scenario whose values and forms are determined as functions of the scenario's input data are called *endogenous*.

Define a *test case* to be a scenario together with input data. A *solution* for a test case is a determination of values and forms for the test-case scenario's endogenous variables and functions, conditional on the test-case input data. A suite of related test cases can be generated for a given scenario by introducing systematic changes in its input data.

The structure of the AMES(V2.01) test bed consists of the exogenous initial system state vector $\mathbf{x}(1)$ together with the exogenous disturbances $\{ \mathbf{w}(D) \mid D = 1,\ldots,DMax \}$. In particular, as previously explained, the state vector $\mathbf{x}(1)$ comprises methods and data for all of the AMES agents at the start of day 1; hence, by necessity, its contents must be exogenously given.

As seen from a backwards recursion of (16), the system state vector $\mathbf{x}(D+1)$ for any day D+1 can in principle be expressed as a function of $\mathbf{x}(1)$ together with the disturbances realized through day D:

$$\mathbf{x}(D+1) \;=\; f(\mathbf{x}(1), \mathbf{w}(1), \ldots, \mathbf{w}(D)) \tag{17}$$

Moreover, suppose the disturbances { $\mathbf{w}$(D) | D = 1,. . .,DMax } are proxied by successive draws from pseudo-random number generators (PRNGs). Then the functional forms of these PRNGs, together with the vector $\mathbf{s}$ of initial seed values for these PRNGs, can be included in $\mathbf{x}(1)$ and the disturbances appearing in (17) can be omitted. For expositional purposes, however, it will continue to be assumed below that these disturbances are externally streamed-in data rather than PRNG-generated data.

Table 1 lists the exogenous variables included in $\mathbf{x}(1)$ for AMES(V2.01), along with their corresponding admissibility restrictions. The latter restrictions are meant to ensure that the particular values selected for the exogenous variables are empirically meaningful.

Test cases can be constructed for AMES(V2.01) by systematically varying the values for any of the exogenous variables in Table 1 within their admissibility limits. In addition, test cases can be constructed for AMES(V2.01) by streaming in systematically varied values for the exogenous disturbances { $\mathbf{w}$(D) | D = 1,. . .,DMax }. Of particular relevance for restructured wholesale power markets are the following types of disturbances: unanticipated changes in fixed demands (loads); unanticipated changes in fuel costs; unanticipated ("forced") generation outages; and unanticipated transmission line losses.

More generally, AMES(V2.01) has been fully developed in Java in order to achieve a modular and extensible architecture. Users can thus develop more sophisticated test cases for AMES(V2.01) that involve changes in the initial forms of the agent methods included in $\mathbf{x}(1)$, not just changes in the initial values of agent data. For example, experiments can be designed to test what happens when agents use structurally distinct forms of learning methods (e.g., VRE-RL versus Q-learning), or when the ISO institutes a change of policy (e.g., a changed supply-offer price cap).

References

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[6] J. Sun and L. Tesfatsion, "DC optimal power flow formulation and solution using QuadProgJ," *Proceedings*, IEEE Power and Energy Society General Meeting, Tampa, Florida, June 2007. Working paper available: www.econ.iastate.edu/tesfatsi/DC-OPF.JSLT.pdf

[7] *AMES Wholesale Power Market Test Bed Homepage*, maintained by L. Tesfatsion at www.econ.iastate.edu/tesfatsi/AMESMarketHome.htm, hosted by the Department of Economics, Iowa State University, Ames, Iowa.

Public Access:

// **Public Methods**
The ***World Event Schedule,*** i.e., a system clock that permits inhabitants to time and synchronize activities (e.g., reporting of bids/offers into the day-ahead market);
Protocols governing trader collusion, insolvency,...;
Methods for receiving data;
Methods for retrieving stored World data.

Private Access:

// **Private Methods**
Methods for gathering, storing, and displaying data;
Methods for managing simulation runs (e.g., stopping rules).
// **Private Data**
World inhabitants (Grid, Day-Ahead Mkt, LSEs, GenCos, ISO);
World inhabitants' methods and data;
Historical data about World events.

Figure 1: The AMES(V2.01) World: A structural agent

Public Access:

// **Public Methods**
Methods for receiving data;
Methods for retrieving stored Transmission Grid data.

Private Access:

// **Private Methods**
Methods for automated gathering, storing, & sending of data;
Methods determining actual flow of power on the grid;
Methods determining physical equipment deterioration.

// **Private Data**
Grid attributes (base voltage/apparent power, reactances,...).

Figure 2: The AMES(V2.01) Transmission Grid: A structural agent

Public Access:

// **Public Methods**
getWorldEventSchedule(clock time);
Protocols governing the reporting of bids/offers;
Protocols governing market clearing, trades, & settlements;
Methods for receiving data;
Methods for retrieving stored Day-Ahead Market data.

Private Access:

// **Private Methods**
Methods for gathering, storing, and sending data.

// **Private Data**
Historical data about LSEs (e.g., demand bids);
Historical data about GenCos (e.g., supply offers);
Address book (communication links).

Figure 3: The AMES(V2.01) Day-Ahead Market: An institutional agent

Public Access:

// **Public Methods**
getWorldEventSchedule(clock time);
getMarketProtocols(reporting of bids/offers, settlement,...);
Methods for receiving data;
Methods for retrieving stored ISO data.

Private Access:

// **Private Methods**
Methods for gathering, storing, and sending data;
Method for solving hourly DC optimal power flow;
Methods for posting schedules and carrying out settlements;
Methods for implementing market power mitigation.

// **Private Data**
Historical data (e.g., cleared bids/offers, LMPs,...);
Address book (communication links).

Figure 4: The AMES(V2.01) ISO: A cognitive agent

Public Access:

// **Public Methods**
getWorldEventSchedule(clock time);
getMarketProtocols(demand bid reporting, settlement,...);
getMarketProtocols(ISO market power mitigation);
Methods for receiving data;
Methods for retrieving stored LSE data.

Private Access:

// **Private Methods**
Method for determining my demand bids;
Method for calculating my net earnings.

// **Private Data**
My downstream demand, grid location, current wealth...;
Historical data (cleared demand bids, LMPs,...);
Address book (communication links).

Figure 5: An AMES(V2.01) LSE: A cognitive agent

Public Access:

// **Public Methods**
getWorldEventSchedule(clock time);
getMarketProtocols(supply offer reporting, settlement,...);
getMarketProtocols(ISO market power mitigation);
Methods for receiving data;
Methods for retrieving stored GenCo data.

Private Access:

// **Private Methods**
Methods for gathering, storing, and sending data;
Methods for calculating my expected/actual net earnings;
Method for updating my supply offers (**LEARNING**).

// **Private Data**
My grid location, cost function, capacity, current wealth... ;
Historical data (cleared supply offers, LMPs, ...);
Address book (communication links).

Figure 6: An AMES(V2.01) GenCo: A cognitive learning agent

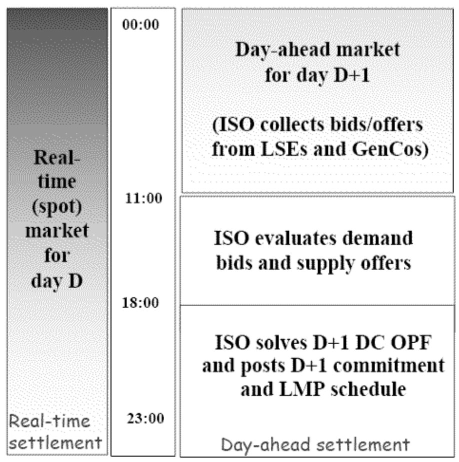

Figure 7: Activities of the AMES(V2.01) ISO during a typical day D

Table 1: Admissible Exogenous Variables for AMES(V2.01)

Variable	Description	Admissibility Restrictions
K	Total number of transmission grid buses	K > 0
N	Total number of physically distinct network branches	N > 0
J	Total number of LSEs	J > 0
I	Total number of GenCos	I > 0
J_k	Set of LSEs located at bus k	$\mathrm{Card}(\cup_{k=1}^{K} \mathrm{J}_k) = \mathrm{J}$
I_k	Set of GenCos located at bus k	$\mathrm{Card}(\cup_{k=1}^{K} \mathrm{I}_k) = \mathrm{I}$
S_o	Base apparent power (in three-phase MVAs)	$\mathrm{S}_o \geq 1$
V_o	Base voltage (in line-to-line kVs)	$\mathrm{V}_o > 0$
V_k	Voltage magnitude (in kVs) at bus k	$\mathrm{V}_k = \mathrm{V}_o$
km	Branch connecting buses k and m (if one exists)	$k \neq m$
BR	Set of all physically distinct branches km, $k < m$	$\mathrm{BR} \neq \emptyset$
x_{km}	Reactance (ohms) for branch km	$\mathrm{x}_{km}=\mathrm{x}_{mk} > 0$, km in BR
B_{km}	$[1/\mathrm{x}_{km}]$ for branch km	$\mathrm{B}_{km}=\mathrm{B}_{mk} > 0$, $km \in \mathrm{BR}$
P_{km}^{U}	Thermal limit (MWs) for real power flow on km	$\mathrm{P}_{km}^{U} > 0$, $km \in \mathrm{BR}$
δ_1	Reference bus 1 voltage angle (in radians)	$\delta_1 = 0$
μ	Penalty weight ($/H·radians) for voltage angle differences in DC-OPF	$\mu > 0$
$\mathrm{P}_{Lj}^{F}(\mathrm{H})$	Hour-H fixed demand (MWs) for LSE j	$\mathrm{P}_{Lj}^{F}(\mathrm{H}) \geq 0$
$\mathrm{SLMax}_j(\mathrm{H})$	Hour-H upper limit for LSE j's price-sensitive demand (MWs)	$\mathrm{SLMax}_j(\mathrm{H}) \geq 0$
$\mathrm{c}_j(\mathrm{H})$,$\mathrm{d}_j(\mathrm{H})$	Hour-H demand coefficients ($/MWh,$/MW^{2}h) for LSE j	$\mathrm{c}_j(\mathrm{H})$,$\mathrm{d}_j(\mathrm{H}) > 0$
$\mathrm{D}_{jH}(\mathrm{p})$	$\mathrm{D}_{jH}(\mathrm{p}) = \mathrm{c}_j(\mathrm{H}) - 2\mathrm{d}_j(\mathrm{H})\mathrm{p}$ = LSE j's hour-H price-sensitive dem. fct. for power p	$\mathrm{D}_{jH}(\mathrm{SLMax}_j(\mathrm{H})) \geq 0$
FCost_i	Hourly pro-rated fixed cost ($/h) for GenCo i	$\mathrm{FCost}_i \geq 0$
Cap_i^{L}	Lower real power operating capacity limit (MWs) for GenCo i	$\mathrm{Cap}_i^{L} \geq 0$
Cap_i^{U}	Upper real power operating capacity limit (MWs) for GenCo i	$\mathrm{Cap}_i^{U} > 0$
a_i,b_i	Cost coefficients ($/MWh,$/MW^{2}h) for GenCo i	$\mathrm{b}_i > 0$
$\mathrm{MC}_i(\mathrm{p})$	$\mathrm{MC}_i(\mathrm{p}) = \mathrm{a}_i+2\mathrm{b}_i\mathrm{p}$ = GenCo i's true MC function for real power p	$\mathrm{MC}_i(\mathrm{Cap}_i^{L}) > 0$
$\mathrm{InitMoney}_i$	Initial money holdings ($) of GenCo i	$\mathrm{InitMoney}_i > 0$
M_i	Cardinality of the action domain AD_i for GenCo i	$\mathrm{M}_i \geq 1$
$\mathrm{M1}_i$,$\mathrm{M2}_i$,$\mathrm{M3}_i$	Integer-valued density-control parameters for AD_i construction	$\prod_{j=1}^{3} \mathrm{Mj}_i = \mathrm{M}_i$
RIMax_i^{L}	Ordinate range-index parameter for AD_i construction	$\mathrm{RIMax}_i^{L} \in [0,1)$
RIMax_i^{U}	Slope range-index parameter for AD_i construction	$\mathrm{RIMax}_i^{U} \in [0,1)$
RIMin_i^{C}	Capacity-withholding range-index parameter for AD_i construction	$\mathrm{RIMin}_i^{C} \in (0,1]$
SS_i	Slope-start control parameter for AD_i construction	$\mathrm{SS}_i > 0$
MaxDNE_i	Estimate of max daily net earnings ($/D) for GenCo i from AD_i	$\mathrm{MaxDNE}_i > 0$
$\mathrm{q}_i(1)$	Initial propensity ($/D) for GenCo i (learning)	$\mathrm{q}_i(1) \propto \mathrm{MaxDNE}_i$
T_i	Temperature cooling parameter for GenCo i (learning)	$\mathrm{T}_i > 0$
r_i	Recency parameter for GenCo i (learning)	$0 \leq \mathrm{r}_i \leq 1$
e_i	Experimentation parameter for GenCo i (learning)	$0 \leq \mathrm{e}_i < 1$
PCap	Price cap ($/MWh) imposed on GenCo supply offers by ISO	PCap > 0