Wholesale Power Price Dynamics Under Transmission Line Limits: A Use of an Agent-Based Intelligent Simulator

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Abstract—This research proposes a use of an agent-based intelligent simulator to numerically examine the influence of a transmission line limit on the dynamics of a wholesale power market. In the proposed simulator, all agents are equipped with learning capabilities. The power market is structured by multiple zones connected by transmission lines. The following business implications are found in this study. 1) The learning speed of reinforcement learning depends upon a dynamic change of market price. 2) The market price and volatility of electricity is increased by a line limit. The increase is influenced by not only a capacity limit but also a zone structure and an amount of demand. 3) The average price and volatility of electricity are influenced by the number of capacity-limited links. 4) There is no major difference between day-ahead (DA) and real-time (RT) markets in terms of the influence of a line limit. 5) There is a slightly increasing trend in average DA and RT market prices along with the percentage reduction of a current line limit.

Index Terms—Agent-based approach, cybernetics, reinforcement learning.

I. INTRODUCTION

DEREGULATION in the U.S. electric power industry has opened many wholesale power trading markets where price setting processes are so complex that most of analytical approaches cannot solve the complexity of power trading [1]. To overcome the difficulty, a new agent-based simulator [2], [3] was developed to investigate a dynamic fluctuation of electricity price. The proposed simulator provided a high level of estimation accuracy to predict a price fluctuation of electricity. However, there was still a major problem in [2] and [3] because a transmission grid system in the power trading scheme was not incorporated, even though the influence of capacity-limited links on market price of electricity was widely known [4], [5].

As an extension of [2] and [3], this research overcomes the difficulty by incorporating transmission links into the agent-based intelligent simulator. This research also reexamines the intelligent simulator from the perspective of “cybernetics” that incorporates a reinforcement learning capability to produce feedback information on a power market. The reinforcement learning serves as a knowledge base for developing agents in the intelligent simulator. Such a learning capability is important because the incorporation of transmission links into the intelligent simulator requests agents to adjust themselves to a dynamic trading environment with line limits. Consequently, the simulator needs to be restructured from a combined perspective of reinforcement learning, knowledge-base development, and cybernetics. Using the proposed simulator, we investigate numerically how a line limit in transmission influences the market price of electricity. That is the purpose of this study.

The remaining structure of this paper is organized as follows. Section II summarizes previous research related to power trading. Section III describes U.S. wholesale power market and how a line limit influences the market. Section IV proposes a market clearing scheme. Section V describes a computer algorithm. Section VI documents a simulation study. Section VII concludes this study and summarizes future research agendas.

II. PREVIOUS RESEARCH

A. Agent-Based Approach

The approach was proposed as a numerical (computer intensive) method to deal with various types of system complexities. Reinforcement learning was often incorporated into agents so they could interact with a dynamic environment [6], [7]. Such applications of the agent-based approach could be found in understanding various market behaviors [8], [9]. The applicability was also found in power trading. For example, the research efforts [10]–[13] examined the dynamic change of a power exchange market, considering that the market was a multiagent adaptive system. Detailed discussions on historical and current issues on the agent-based approach could be found in [14]–[17].

B. Simulators for Power Trading

Several simulators were developed for agent-based power trading. First, PowerWeb, developed at Cornell University [18], was designed to understand various power markets with human decision makers who interacted with each other in a Web-based tool. Second, Agentbuilder [19] utilized decision theory and used three strategies for power trading. Third, the simulator for electrical power industry agents (SEPIA) [20] included agents who used discovery informatics to develop and identify patterns in a power trading environment. Fourth, the multiagent simulation system for competitive electricity markets (MASCEM) [21] was a market simulator that used open
TABLE I
COMPARISON AMONG AGENT-BASED POWER TRADING SIMULATORS

<table>
<thead>
<tr>
<th>Software</th>
<th>Estimation</th>
<th>Transmission</th>
<th>Decision Making</th>
<th>Analysis</th>
<th>Intelligence</th>
</tr>
</thead>
<tbody>
<tr>
<td>PowerWeb</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Agentbuilder</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>SEPIA</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>MASCEM</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>EMCAS</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>MAIS</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

agent architecture to create a rule-based power trading system. Fifth, the electricity market complex adaptive system (EMCAS) [22] used a complex adaptive system to represent agent learning and adaptation. Finally, the multiagent intelligent simulator (MAIS), proposed by the authors of this study [2], [3], had three types of agents who were equipped with various learning capabilities. In [2], all agents interacted with a power market, using only a self-learning capability. To extend [2], the research [3] developed two types of agents who incorporated limited and multiple reinforcement learning capabilities, respectively. Both capabilities were used for an interaction with a power market.

Table I compares the agent-based power trading simulators described earlier. Each simulator is evaluated from the five desirable capabilities such as: 1) estimation; 2) transmission; 3) decision making; 4) analysis; and 5) intelligence. Table I indicates the availability (yes or no) of each desirable capability. First, all the existing simulators, except MAIS, do not have an estimation capability to predict market price of electricity. Second, all the existing simulators do not have a numerical capability regarding how a capacity limit on transmission influences wholesale price of electricity. Third, most of the agent models use a probabilistic model in order to investigate agent’s bidding decision and a monotonically increasing utility function to represent decision-making capability. Fourth, it is important to have an analytical (or sensitivity) capability that can explore a dynamic change of a power market by changing parameters related to the power market. Finally, artificial intelligence (AI) technique has to be incorporated for agent’s adaptive behavior.

C. Contribution of This Research

All the previous research on agent-based power trading and simulators did not consider how a capacity limit on transmission influences market clearing process of electricity. This study discusses first the influence of a transmission limit on a price-setting process of electricity.

D. Reinforcement Learning for Cybernetics

In the previous studies on reinforcement learning, agents interacted with not only an environment (e.g., an electric power market) but also other agents. The interaction with other agents influenced the decision-making processes of an agent to be examined. For example, [23] used a game theoretical perspective for agent interaction. The research [24] discussed negotiation among agents in a complex organizational context. An interaction among agents via a computer system was discussed in [25]. Furthermore, the previous research explored how to incorporate knowledge management into agent-based approach [26].

E. Position of This Research

We do not explore the direct interaction among agents, rather focusing upon the interaction between each agent and a power market as an environment. Thus, agents in this study have an indirect contact with others via win–lose experience in a wholesale market of electricity. Moreover, this study considers that a knowledge base incorporated in each agent is gradually developed by a series of win–lose experiences. The trading experience is a main source of agent’s reinforcement learning. Thus, the knowledge base for an agent can be considered as an intelligent product of “cybernetics” in this study, because the trading experience consists of feedback information for each agent. This type of research cannot be found in the previous research on reinforcement learning.

III. U.S. WHOLESALE POWER MARKET

A. Wholesale Market of Electricity

The U.S. wholesale power market is functionally separated into: 1) a power exchange market and 2) a transmission market. The power exchange market is further functionally broken down into: 1) a real-time (RT) market; 2) a day-ahead (DA) market; and 3) a long-term bilateral or multilateral exchange market.

The DA is “financial and forward” because all the transactions in the DA stop one day prior to the day of actual transaction. Furthermore, the bidding decisions on the DA are determined by the speculation of traders. Meanwhile, the RT is a “physical and spot” market because the delivery of power in the RT is not optional like in the DA. All traders in the RT know the actual demand of electricity. Hence, the aspect of financial speculation is very limited in RT. Thus, RT is a physical market. In RT, traders need to make their decisions within a very limited time. Consequently, it is a physical spot market in this study. Such auction markets are usually controlled by independent system operator (ISO) and regional transmission organization (RTO) such as Pennsylvania–Jersey–Maryland (PJM).

B. Line Limits in Transmission Among Multiple Zones

In this study, a wholesale power exchange market is separated into multiple zones based on the geographic location of nodes and a transmission grid structure. Each zone consists of several generators and loads. There are two types of transmission connections: intrazonal link and interzonal link. Intrazonal links are connections that exist among generators and loads within a zone. Interzonal links are connections that exist between zones. A common market clearing price (MCP) exists if these zones are linked together with each other. However, if these are functionally separated by a capacity limit on an interconnection line, then these zones have different locational marginal prices (LMPs) as MCP.

To explain why we need to consider the influence of capacity limits on transmission on a wholesale power market, we
consider the wholesale market operated by California ISO as a real example. The market is divided into three zones for the purposes of pricing: NP15 is in the north, SP15 is in the south, and ZP26 is in the center of the state. The central zone (ZP26) has only two transmission links, one to northern path (NP15) and one to southern path (SP15). The northern path and southern path are not directly connected to each other. If they need excess electricity, they have to obtain it from other states as shown in Fig. 1.

1) Why does the proposed agent-based simulator for power trading need to consider multiple zones?: All the U.S. wholesale markets are controlled by ISO or RTO, as mentioned previously. For example, California ISO controls the three zones, as depicted in Fig. 1. (PJM controls 17 zones for the determination of LMPs.) Thus, there is no single LMP that can be used as a common market price for the entire region of California. Hence, the proposed simulator needs to consider multiple zones in the price setting scheme of wholesale electricity. That is the reality of power trading.

2) What is the influence of considering multiple zones?: Generators in each zone provide electricity for not only its own zone but also another zone(s) if a link is connected between the zones. For example, generators in NP15 can participate in the wholesale market of ZP26 because the two zones have a link connection. This indicates that the LMP of ZP26 is determined by bids of generators in both ZP26 and NP15 as a supply side. Thus, the LMP of ZP26 is influenced by market fundamentals (e.g., weather, temperature, and demographic/economic changes) of NP15. In particular, when the proposed simulator incorporates multiple zones in a power trading market, the simulator needs to determine the number of generators in multiple zones who can participate in the determination of each LMP setting process. The number of generators is given in the case of a single market [2], [3]. However, in the case of multiple zones, the number of generators is unknown and determined under a dynamic change of market conditions in other zones. Such a difference is the influence of considering multiple zones.

3) What is the effect of considering capacity limits on transmission lines?: The line limit in transmission influences the selection of generators that can participate in a market clearing process of each zone, as mentioned earlier. When a capacity limit exists on links, ISO often selects expensive generator(s), within the zone, for power supply. As a consequence of selecting an expensive generator, the LMP is usually increased from the market price under no line limit. Thus, the price increase of wholesale electricity is the effect of the capacity limit on transmission.

4) Why does ISO select expensive generators for power supply?: Inexpensive generators such as nuclear plants and hydroelectric dams usually locate in rural areas. In contrast, expensive generators such as fossil-fuel plants and hydroelectric dams usually locate near urban areas. If ISO does not find any transmission difficulty from an inexpensive generator in a rural area to a load (for consumption) in an urban area, then ISO selects the inexpensive generator as a power supplier. However, if ISO finds the transmission difficulty between urban and rural areas, ISO must select an expensive generator located near the urban area in order to avoid the transmission problem. Consequently, LMP in the urban area increases because of the expensive generator. Thus, the transmission is a major component of auction-based power trading.

Fig. 2 illustrates an algorithm for clearing a wholesale power market with multiple zones at the tth delivery period. This algorithm is applicable to both the DA and RT. In the algorithm, the wholesale market is separated into Z zones. Every zone is connected to one another by means of a link. Fig. 2 assumes that all links are not limited. Then, the assumption is dropped...
Fig. 2. Market clearing scheme for multiple zones. Legend: AG, allocated generator; UAG, unallocated generator; C, cleared zone; NC, not cleared zone; PG, participating generator; TCG, transmission-connected generator; MCPG, market clear participating generator.

in the algorithm to investigate the influence of a capacity limit on the MCP.

The subscripts \((z = 1, 2, \ldots, Z\) and \(t = 1, 2, \ldots, T\) used in Fig. 2 indicate the \(z\)th zone and the \(t\)th delivery period of electricity, respectively. The other subscripts \(i(z) = 1(z), 2(z), \ldots, n(z)\) and \(j(z) = 1(z), 2(z), \ldots, k(z)\) indicate the \(i\)th generator and the \(j\)th wholesaler in the \(z\)th zone, respectively. The number of generators and wholesalers depend upon the zone. To avoid a descriptive duplication, this study omits the description on these subscripts as much as possible.
However, we add the description if explanatory necessity occurs in this paper.

Fig. 2 has the following four sets at the initial preprocessing stage: AG represents a set of generators that are allocated for current generation, UAG represents a set of generators that are not allocated for current generation, C represents a set of cleared zones, and NC represents a set of zones that are not cleared.

As the preprocessing process, ISO forecasts a total demand \( D_{(z,t)} = \sum_j d_{(j,z)} \), where \( d_{(j,z)} \) is the demand forecast from the \( j \)th wholesaler in the \( z \)th zone. The total supply \( S_{(z,t)} \) obtained from all generators in the \( z \)th zone is \( S_{(z,t)} = \sum_i s_{(i,z)}^{m} \), where \( s_{(i,z)}^{m} \) is the maximum generation capacity of the \( i \)th generator in the \( z \)th zone. This study assumes that the total sum of maximum generation capacities \( \left( \sum S_{(z,t)} \right) \) is larger than or equal to that of total forecasted demand \( \left( \sum D_{(z,t)} \right) \). An excess amount of power supply is \( E_{(z,t)} = S_{(z,t)} - D_{(z,t)} \).

In the algorithm, a zone is said to be “cleared” if all the load requirements in the zone are satisfied. That is, if \( S_{(z,t)} \geq D_{(z,t)} \), then the \( z \)th zone can be cleared at the \( t \)th period. Otherwise, i.e., \( S_{(z,t)} < D_{(z,t)} \), the zone is not cleared. In this case, ISO arranges an additional amount of electricity by using extra (usually expensive) generators within its own zone and/or obtaining electricity from other linked zones. In the former case, ISO needs to reexamine the selection of generators and dispatch scheduling within its own zone. In the latter case, ISO needs to examine whether unused generators are available in other zones.

This initial clearing process of Fig. 2 continues sequentially for all zones, as depicted in the upper part of the figure. At the end of the initial market clearing process, all the zones are cleared for all zones, as depicted in the upper part of the figure. At the end of the initial market clearing process, all zones work as a single market entity and they have a single MCP. Meanwhile, trading auction under a line limit is much complicated than that of no line limit.

To explain the auction process under the line limit, let us select the \( z \)th zone from NC. Then, at the \( t \)th period, \( n(z) \) generators for \( i(z) = 1(z), \ldots, n(z) \) are selected from MCPG and \( k(z) \) wholesaler for \( j(z) = 1(z), \ldots, k(z) \) are selected from within the \( z \)th zone. Both generator and wholesaler groups enter a market clearing process in order to clear the \( z \)th zone at the \( t \)th period.

1) Supply Side in DA: All the generators are classified into two groups: generators within the \( z \)th zone and generators in the other zones. The \( i \)th generator is selected from the \( z \)th zone, and the generator bids \( s_{(i,z)}^{m} \) for \( D_{(i,z)} \). The \( j \)th wholesaler selects from within the \( z \)th zone, the \( j \)th wholesaler bids \( e_{(j,z)} \) for \( D_{(j,z)} \). The \( z \)th zone is not influenced by the line limit. The \( z \)th zone is a single market entity and they have a single MCP. Meanwhile, trading auction under a line limit is much complicated than that of no line limit.

2) Demand Side in DA: At the beginning of the \( t \)th period, the \( j \)th wholesaler is selected from within the \( z \)th zone, and he predicts a bidding price \( w_{(1,j,z)} \) using the function \( F \) of demand \( w_{(1,j,z)} = F(e_{(j,z)}) \). Here, \( e_{(j,z)} \) is a demand estimate for DA (see [2, Fig. 4] that visually describes the
function). The wholesaler bids \(d(1)_{j(z,t)}\) for DA in the range \((d(1)_{j(z,t)} \leq e_{j(z,t)})\). The bidding amount is expressed by \(d(1)_{j(z,t)} = \delta_{j(z,t)} r_{j(z,t)}\). Here, \(\delta_{j(z,t)} (0 \leq \delta_{j(z,t)} \leq 1)\) is a decision parameter to express how the bid is strategically reduced from the demand estimate. The \(i\)th wholesaler does not need to satisfy the demand estimate in DA, because he has another chance to bid in the RT. Similarly, a bidding price for demand is determined by \(p(1)_{j(z,t)} = \lambda_{j(z,t)} q_{j(z,t)}\). Here, \(\lambda_{j(z,t)} (0 \leq \lambda_{j(z,t)} \leq 1)\) is a decision parameter for price adjustment from the estimated price. After both \(d(1)_{j(z,t)}\) and \(p(1)_{j(z,t)}\) are submitted to ISO, the DA market determines \(\hat{p}(1)_{i(z,t)}\) (an MCP of DA for the \(z\)th zone at the \(t\)th period), \(\hat{s}(1)_{i(z,t)}\) (a power allocation to the \(i\)th generator in DA) and \(\hat{d}(1)_{j(z,t)}\) (a power allocation to the \(j\)th wholesaler in DA), along with \(\hat{s}(1)_{i(z',z-1,t)}\) (a power allocation from the \(i\)th generator at the \(z\)'th zone for transmission to the \(z\)th zone in DA).

3) Supply Side in RT: If the \(i\)th generator is selected from the \(z\)th zone, then he bids \(s(0)_{i(z,t)}(= s(m)_{i(z,t)} - \hat{s}(1)_{i(z,t)})\) in RT, where “0” within parentheses indicates RT. Meanwhile, if the \(j\)th generator is selected from the \(z\)'th zone, then the bidding amount becomes \(s(0)_{i(z',z-1,t)} = \min(s(m)_{i(z',z-1,t)} - \hat{s}(1)_{i(z',z-1,t)}, \hat{d}(1)_{j(z,t)} - \hat{s}(1)_{i(z',z-1,t)})\). The bidding amount is determined by considering both the remaining generation capacity after DA (= \(s(m)_{i(z',z-1,t)} - \hat{s}(1)_{i(z',z-1,t)}\)) and the maximum transmission capacity after DA (= \(\hat{d}(1)_{j(z,t)} - \hat{s}(1)_{i(z',z-1,t)}\)). The pricing strategy of the generator is expressed by \(p(0)_{i(z,t)} = MC_{i(z,t)}/(1 - \eta_{i(z,t)})\), where \(\eta_{i(z,t)}\) is a markup ratio \((0 \leq \eta_{i(z,t)} < 1)\) and \(p(0)_{i(z,t)}\) is a bidding price for the RT.

4) Demand Side in RT: All the wholesalers must deliver the amount of electricity demanded by end users. Therefore, they bid only their amounts, but not prices, in the RT, because it is a physical market. Therefore, they specify only the purchasing amount \(d(0)_{j(z,t)}(= r_{j(z,t)} - \hat{d}(1)_{j(z,t)})\) in the RT, where \(r_{j(z,t)}\) is real demand on the delivery day and \(\hat{d}(1)_{j(z,t)}\) is an amount of power allocation in the DA. ISO adjusts all the requests on power allocation in order to determine \(\hat{d}(0)_{j(z,t)}\) (a power allocation to the \(j\)th wholesaler in the RT) and \(\hat{p}(0)_{i(z,t)}\) (MCP in the RT of the \(z\)th zone at the \(t\)th period) through a market mechanism. The ISO also determines \(\hat{s}(0)_{i(z',z-1,t)}\) (a power allocation to the \(i\)th generator in the RT) and \(\hat{s}(0)_{i(z',z-1,t)}\) (a power allocation from the \(i\)th generator at the \(z\)'th zone for transmission to the \(z\)th zone in the RT).

5) Auction Process Within ISO: In DA of the not-cleared \(z\)th zone, generators submit their bidding amounts and prices. Here, generators that can participate into the DA belong to MCPG. Similarly, wholesalers bid their amounts and prices, where all wholesalers belong to the \(z\)th zone. The ISO reorders their bids from both generators and wholesalers. The supply side combinations are reordered according to the ascending order of these bidding prices. Meanwhile, the demand side combinations are reordered according to the descending order of these bidding prices.

In the RT of the \(z\)th zone at the \(t\)th period, generators bid their prices and quantities, but wholesalers submit only their demands, not the bidding prices. The RT market is a physical market where the demand of end users must be satisfied (see [2, Figs. 1–3] that visually describe the auction process of DA and RT).

B. Adaptive Behavior of Agents Equipped with Learning Capabilities

In the simulator, each zone consists of many agents (as generators and wholesalers) who can accumulate knowledge from their bidding results in order to adjust their proceeding bidding strategies. As depicted in Fig. 3, the agents operate in two modes: practice and real experience. During a practice period, the agents use nonreinforcement learning where they know their win or lose results, but they do not access any information on market price of electricity and power allocation between generators and wholesalers. Since the power market is considered as an environment in this study, the market price and power allocation become feedback information from the wholesale market of electricity. The nonreinforcement learning is separated into three processes: 1) knowledge generation; 2) knowledge accumulation; and 3) knowledge creation. Since there is no feedback from the market, each agent has to generate knowledge by himself. This process is a self-learning process. The purpose of knowledge generation process is to discover and establish his initial bidding strategy. The agent bids in the markets (DA and RT) by changing decision parameters and markup ratios using a random distribution on (0,1).

After bidding, the values of parameters and their win–lose results are stored in the knowledge accumulation process. The accumulated knowledge is further processed by using a sigmoid decision rule (speculation on a winning probability) and an exponential utility function (risk preference). This process is knowledge creation. The nonreinforcement learning is repeated until the practice period is over.
After the practice period is completed, each agent starts real trading experience. The bidding decisions during the real experience period are based upon previous trading practice. The real experience period follows reinforcement learning because the agents react according to the feedback information (market price and power allocation) obtained from the wholesale markets (an external environment). The reinforcement learning is functionally separated into three processes: 1) knowledge utilization; 2) knowledge accumulation; and 3) knowledge creation. In the knowledge utilization, each agent fully utilizes both the processed information from the previous knowledge creation process in the practice period and the feedback information from the markets in the real experience period in order to decide his bidding strategy. Based on the feedback from the markets, the agents change the value of decision parameters according to the reinforcement learning algorithm. The win–lose results, market price, and power allocation as well as the corresponding decision parameter values are stored in a knowledge base at his knowledge accumulation process. The knowledge accumulation and knowledge creation processes are similar to those of the practice period. The entire reinforcement learning is repeated until all iterations are completed.

1) Reward to Agent: Table II summarizes a reward of the ith generator. Each cell of Table II indicates a winning reward of the generator. For example, if \( \hat{p}(1)_{z(t)} < p(1)_{j(z)} \), then he cannot have any chance to generate electricity, so having no reward in the DA. In contrast, if \( \hat{p}(1)_{z(t)} \geq p(1)_{j(z)} \), then he receives a reward \( (\hat{p}(1)_{z(t)} - MC_{i(z)} \hat{s}(1)_{i(z)}) \), as listed in the cell under “DA” and “within the z zone.” In a similar manner, if \( \hat{p}(0)_{i(t)} \geq p(0)_{j(z)} \) in the RT, then he obtains \( (\hat{p}(0)_{i(t)} - MC_{i(z)} \hat{s}(0)_{i(z)}) \). The two types of sale occur within the ith zone. If the generator sells electricity to the zth zone, he can obtain a reward from the zone. In this case, the reward becomes \( (\hat{p}(1)_{z(t)} - MC_{i(z)} \hat{s}(1)_{i(z) \rightarrow z'}) \) in DA and \( (\hat{p}(0)_{i(t)} - MC_{i(z)} \hat{s}(0)_{i(z) \rightarrow z'}) \) in RT. Here, \( \hat{s}(1)_{i(z) \rightarrow z'} \) and \( \hat{s}(0)_{i(z) \rightarrow z'} \) are the amount of electricity transmitted for the DA and the RT, respectively, from the ith zone to the zth zone. The transmission from one zone to another zone is associated with a unit transmission cost that is listed as \( TC_{i(z) \rightarrow z'} \) in Table II. The total reward \( (R_{i(z)}) \) for the ith generator in the zth zone is determined by subtracting the transmission cost from a sum of these sales. The transmission cost within a same zone is zero.

<table>
<thead>
<tr>
<th>TABLE II</th>
<th>REWARD FOR GENERATOR</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Sale</strong></td>
<td>DA</td>
</tr>
<tr>
<td>Within the zone</td>
<td>( \hat{p}(1)<em>{z(t)} - MC</em>{i(z)} \hat{s}(1)_{i(z)} )</td>
</tr>
<tr>
<td>Transmission ((z \rightarrow z'))</td>
<td>( \hat{p}(1)<em>{z(t)} - MC</em>{i(z)} \hat{p}(1)_{z \rightarrow z'} )</td>
</tr>
<tr>
<td><strong>Cost</strong></td>
<td>( \hat{s}(1)<em>{i(z) \rightarrow z'} + \hat{s}(0)</em>{i(z) \rightarrow z'} )</td>
</tr>
</tbody>
</table>

The important feature of [2] and [3] is that [2] has investigated an adaptive sigmoid decision rule and an exponential utility function. Since the study [3] describes the two adaptive behaviors of agents (referred to as types I and II), we do not describe them except providing brief comments on them.

First, the adaptive learning process of type I (not type II) is used in this study. In type I, each agent constantly looks for an increase in an estimated winning probability. In other words, the agent looks for a combination of unknown parameters that can increase a winning probability. The win or lose of each trade is considered as a binary response. The proposed simulator incorporates a sigmoid model into each agent to express such an occurrence of the binary response that is widely used to predict a winning probability. Mathematically speaking, the sign of each parameter estimate provides information regarding which decision parameter needs to be increased or decreased. However, the winning probability, obtained from the sigmoid model, does not immediately imply that the agent can always win in a wholesale market with the estimated probability. That is theoretical speculation. The win or lose is determined through the DA and RT market mechanism.

Second, all the agents (type I in [3]) in the proposed simulator have an exponential utility function that represents a risk aversion preference.

C. Features Extended From Previous Simulator

As mentioned previously, this study discussed two major extensions from [2] and [3]: 1) single zone versus multiple zones and 2) a capacity limit on transmission links (that yield a “market divide” where different zones have different market prices). The important feature of [2] and [3] is that [2] has investigated the adaptive behavior of agents who have only a self-learning capability via win–lose experience. The research [3] extended [2]...
in the manner that we examined the adaptive behavior of agents with reinforcement learning, considering two different groups of agents (types I and II). Agents in the second group incorporated a price estimation capability. Meanwhile, the first group incorporated an exponential utility function and a market speculation capability in addition to the price estimation capability. Thus, [3] was interested in different adaptive behaviors of agent groups. That was a difference between [2] and [3]. We are not interested in the adaptive behaviors of agents as explored in [2] and [3]. Rather, we are interested in how a capacity limit on transmission influences the market clearing process of wholesale power trading.

In addition to the aforementioned differences, this study needs to mention the following algorithmic features that cannot be found in the previous works [2], [3], returning to Fig. 2. First, the studies [2], [3] consider only the AG because the number of generators is given to the simulator. All the generators participate in a single zone market. Consequently, [2] and [3] do not need a market clearing scheme depicted in Fig. 2. In contrast, this study needs to consider six different sets (AG, UAG, C, NC, PG, and MCPG) because the number of generators, who can participate in each zone, depends upon line connections among zones and a capacity limit on lines. Second, the bidding strategy and speculation of agents (generators and wholesalers) is influenced by both how many agents participate into a market and who are such participating agents. Both are influenced by the line connections among zones and the capacity limit on lines. Hence, the bidding strategy and speculation of agents in this study are different from those of [2] and [3]. The market clearing process discussed in this study is more complicated than that of [2] and [3].

VI. SIMULATION STUDY

A. Agent Implementation in Proposed Simulator

This study needs to describe how agents are incorporated in the algorithm for clearing multiple zones, as depicted in Fig. 2. First, the proposed simulator generates various agents (as artificial traders) who are equipped with learning capabilities. These agents are categorized by either generators or wholesalers in the simulator. So, there is no consumer in this study. The demand at end users is prescribed for operating the simulator. The number of generators and wholesalers in each zone are given and listed at each simulation study (e.g., Figs. 6 and 7).

Second, we need to specify bidding conditions: \((s_{it}^{m}(z_{t}), MC_{i}(z_{t}), e_{it}(z_{t}), w_{it}(z_{t}), r_{it}(z_{t}))\) for each agent at each zone. Markup ratios and other decision parameters \((\alpha_{it}, \beta_{it}, \eta_{it}, \delta_{it}, \lambda_{it})\) are all unknown. Hence, those need to be initialized as random numbers on \([0, 1]\) in the knowledge generation process of Fig. 3. The simulator creates various bidding strategies for generators and wholesalers by changing these magnitudes. These parameters converge gradually by the win–lose experience of agents in their own bidding processes (reinforcement learning through an interaction with a power market).

Third, as depicted in Fig. 2, the ISO opens a power exchange market for each zone, considering line capacities for transmission among zones. The market clearing process at each zone determines which generators and wholesalers win or lose in each market. Thus, the adaptive behavior of each agent is visually summarized in Fig. 3. All agents are controlled by ISO whose market clearing process is summarized in Fig. 2.

Finally, C# (Microsoft.NETFramework1.1) is the programming language used for the proposed simulator (source: http://msdn.microsoft.com/netframework).

B. Does the Learning Speed of Reinforcement Learning Depend Upon a Dynamic Change of Market Price?

To investigate the aforementioned assertion, we use a real dataset on the California electricity market that are available from the University of California Energy Institute Web site. This data consist of all information like time of transaction, date of transaction, price at each zone in the DA and RT markets, unconstrained price and quantity of the system, import/export quantities in each zone, and prices of various auxiliary services. Each sample represents hourly prices representing 24 h/day. We sample the DA and RT prices in NP-15 and SP-15 from April 1, 1998 to January 31, 2001. A dataset on the DA and RT in ZP-26 are sampled from February 1, 2000 to January 31, 2001. For all the DA markets, a maximum price of $2499.58 was observed at 7 P.M. on January 21, 2001. All the RT markets had a maximum price of $750, starting from June 26, 2000. The prices started rising steadily from May 4, 2000 and ended in January 31, 2001.

Since we do not have exact composition about the market from 1998 to 2001, we use the information provided by California Energy Commission on their Web site for 2005. The Web site provides an approximate composition of the market. There were 964 generators among which 343 were hydroelectric with 20% market capacity, 44 were geothermal with 3% market capacity, 373 were oil/gas with 58% market capacity, 17 were coal with 6% market capacity, 94 were wind with 4% market capacity, 80 were waste-to-energy (WTE) with 2% market capacity, 2 were nuclear with 7% market capacity, and 11 were solar with 1% market capacity. Meanwhile, there were a total of 48 wholesalers. Pacific Gas and Electric had 30% of the share, San Diego Gas and Electric had 7% of the share, Southern California Edison had 51% of the share, Los Angeles (LA) Department of Water and Power had 9% of the share, Sacramento Municipal Utility District had 4% of the share, California Department of Water Resources had 3% of the share, and other 41 utilities had a 12% share. Self-generating agencies accounted for 4% of the share.

Fig. 4 indicates the learning speed of an agent on the markup ratio (\(\beta\)) before the electricity crisis (April 1998–May 2000).
Fig. 5 indicates the learning speed during the crisis (May 2000–January 2001). Table IV summarizes learning speeds of all decision parameters and markup ratios. The averages, listed at the bottom of Table IV, imply that the mean for generators is computed from 289,200 trades \[= 964 \times 3 \times 100 \text{ (replications)} \], and the mean for wholesalers is computed from 14,400 traders \[= 48 \times 3 \times 100 \text{ (replications)} \].

1) **Finding 1**: Table IV, along with Figs. 4 and 5, indicates that the learning speed of reinforcement learning incorporated into agents depends upon the market price change of wholesale electricity. For example, the decision parameter (\(\alpha\)) of generators has 62 (iterations) on average before the crisis and the average is increased to 119 (iterations) during the crisis. We observe the similar results on all the other parameters and markup ratios in both generators and wholesalers. The wholesale price increased 270% and drastically fluctuated during the electricity crisis period.

C. Does a Line Limit Increase the Market Price and Volatility of Electricity Under Different Zone Structures?

This study expects that a line limit influences the market price. However, no one knows how much the price is increased by the line limit. Hence, the numerical assessment is important. This study examines the aforementioned assertion by conducting experiments under three different zone structures in the DA. Fig. 6 depicts the three different market structures used in this simulation. Each DA market is classified into two types of zones: city and rural. The city zone corresponds to a zone with a large population such as NP15 and SP15 in Fig. 1. The rural zone corresponds a zone market where generators export electricity to the city zone. Examples of the rural are summit and four corners in Fig. 1. All rural zones have excess supply and all city zones have excess demand. Each city zone does not have self-sufficient power to satisfy its customers, so the city zone depends on supply from other connected zones.

The number of generators and wholesalers in each zone of each market is specified in Fig. 6. All generators are assumed to have a marginal cost of $20/MWH in rural zones and $35/MWH in city zones. The upper limit on the bidding price is set to $80/MWH. The total maximum generation capacities in two-zone, three-zone, and four-zone markets are 6000, 8000, and 14500 MW, respectively. The total market demand (\(D\)) is expressed as a ratio of total supply (\(D = 50\%S, 60\%S, 70\%S, 80\%S, 90\%S, \text{ and } 100\%S\)), where \(S\) stands for total supply (a total generation capability). For example, \(D = 50\%S\) implies that a total amount of demand is 50% of total supply.

Fig. 6 shows the snapshot of the three market types when \(D = 100\%S\). The supply and demand are distributed among the zones as depicted in Fig. 6. For example, the two-zone market consists of one city zone and one rural zone. The rural zone consists of 10 generators and 20 wholesalers. The total supply (3000 MW) is evenly distributed to the generators maximum supply in each zone. Each generator has a maximum supply of 300 MW (3000 MW divided by 10 generators) in the rural zone. Each wholesaler has an equal maximum demand of 40 MW (max: 800 divided by 20 wholesalers). It should be noted that these numbers specify the upper limits in supply and demand. The individual supply and demand in each delivery period is varied according to the decision parameters of each agent. There is only one link between the city and rural zones. The “X” symbol indicates that there is a capacity limit on the link. For validating this assertion, only one link is capacity limited in all zones.
Table V summarizes average market price and volatility of wholesale electricity in the three zone structures in DA. Here, “average” and “volatility” imply the mean and variance of 100 replications times the number of zones. The left hand side of Table V indicates total amount of demand \( D \) expressed as a ratio of the total supply \( S \).

1) **Finding 2**: The market price is influenced not only by a capacity limit on the link but also by a zone structure. This finding is obtained from Table V. In the two-zone market, when demand closes supply, a capacity limit on the link increases the average and volatility of market price. It is seen from Table V that when \( D = 90\%S \) and \( D = 100\%S \), market prices under no line limit are $28.45/MWH and $29.44/MWH, respectively. The corresponding market prices under a line limit are $47.78/MWH and $80.00/MWH, respectively. There is also a corresponding change in volatility. The market prices under the line limit are sharply increased from the ones under no line limit. Furthermore, the market price under the line limit and \( D = 100\%S \) attains $80.00/MWH, which is the maximum bidding price. This indicates an occurrence of congestion on the link between the two zones. The occurrence increases the average price and volatility of electricity.

When the demand is significantly less than supply (e.g., \( D \leq 70\%S \)), we cannot find a similar result identified for \( D \geq 80\%S \). Moreover, this result (i.e., a line limit increases market price) related to the market with two zones cannot be found in the other market structures (with three zones or four zones). A major change does not occur on average price and volatility of electricity in the other market structures. This result indicates that in markets with more than two links (three-zone and four-zone markets), electricity can be delivered through the other link even if one link is congested. In Fig. 6, the finding can be confirmed for three-zone market by the fact that if the link between C(1) and R(1) is limited, unallocated generators from R(2) can supply electricity to C(1). Even if there is an influence of the line limit on market price, the impact with more than three zones is not as large as that of the two-zone market.

2) **Practical Implication 1**: A transmission limit increases market price and volatility. However, the influence of the line limit depends upon both a market structure (e.g., the number of zones) and an amount of demand. It is a surprising finding that the line limit has more influence on volatility than market price when the number of zones is small. Considering the reality of power trading, we know that a supply side has a generation limit, but a demand side does not have any limit on consumption. The amount of consumption depends upon uncontrollable factors such as a temperature. To maintain the price stability of ISO, each zone needs to have more transmission linkages with other zones. Thus, federal and local governments need to provide transmission investors with various financial incentives (e.g., tax reduction and low interest loan) to build more transmission lines among zones.

**D. Do Market Price and Volatility of DA Depend Upon the Number of Capacity-Limited-Links?**

In the previous assertion, the market price and volatility were examined when only one transmission link was capacity limited. Next, we are interested in an impact on market price and volatility when many links are capacity limited. Fig. 7 depicts DA that consists of five zones (two city and three rural zones). Using this zone structure, we investigate whether market price and volatility of wholesale electricity are influenced by the number of capacity-limited links. This study gradually increases the number of such limited links from 0 to 5 in order to examine the assertion. The capacity-limited links are labeled from 1 to 5, and the corresponding upper limits are indicated in Fig. 7.

Table VI summarizes average price and volatility in the DA under six different line limit conditions. Initially, none of the links are assumed to have a capacity limit. Each link is gradually assigned upper limits until all links are capacity limited. For example, the term “1, 2” in Table VI indicates that the upper limits on link 1 and link 2 are 2500 and 1000 MW, respectively. There is no upper limit on links 3, 4, and 5.

1) **Finding 5**: The average price and volatility of the DA are influenced by the number of capacity-limited links. The rate of increase in both measures is also influenced by the number of limited links and/or a ratio of total demand to total supply. For example, see the last row \( (D = 100\%S) \) of Table VI in which the average price under no line limit is $33.13 ($/MWH) and that of the five limited lines is $78.69 ($/MWH). The average price becomes more than twice due to the change in the number of capacity-limited links. Another interesting finding in Table VI
TABLE VI
AVERAGE PRICE AND VOLATILITY IN DA FOR A FIVE-ZONE MARKET

<table>
<thead>
<tr>
<th>Total Demand</th>
<th>No Line Limit</th>
<th>Line Limit</th>
<th>Average Price (Variance)</th>
</tr>
</thead>
<tbody>
<tr>
<td>D = 50% S</td>
<td>24.65</td>
<td>24.13</td>
<td>24.34</td>
</tr>
<tr>
<td></td>
<td>(14.81)</td>
<td>(9.13)</td>
<td>(39.90)</td>
</tr>
<tr>
<td>D = 60% S</td>
<td>24.93</td>
<td>25.51</td>
<td>35.16</td>
</tr>
<tr>
<td></td>
<td>(19.80)</td>
<td>(16.13)</td>
<td>(40.13)</td>
</tr>
<tr>
<td>D = 70% S</td>
<td>24.98</td>
<td>25.13</td>
<td>37.65</td>
</tr>
<tr>
<td></td>
<td>(22.69)</td>
<td>(22.69)</td>
<td>(38.22)</td>
</tr>
<tr>
<td>D = 80% S</td>
<td>25.80</td>
<td>27.33</td>
<td>50.63</td>
</tr>
<tr>
<td></td>
<td>(32.22)</td>
<td>(33.17)</td>
<td>(55.12)</td>
</tr>
<tr>
<td>D = 100% S</td>
<td>33.13</td>
<td>39.15</td>
<td>49.45</td>
</tr>
<tr>
<td></td>
<td>(34.14)</td>
<td>(69.43)</td>
<td>(70.12)</td>
</tr>
</tbody>
</table>

TABLE VII
AVERAGE WHOLESALE PRICE OF FIVE ZONES (DA)

<table>
<thead>
<tr>
<th>Total Demand</th>
<th>Zones</th>
<th>No Line Limit</th>
<th>Line Limit</th>
<th>Average Price (Variance)</th>
</tr>
</thead>
<tbody>
<tr>
<td>D = 60% S</td>
<td>C(1)</td>
<td>28.85</td>
<td>30.85</td>
<td>48.76</td>
</tr>
<tr>
<td></td>
<td>C(2)</td>
<td>27.08</td>
<td>30.56</td>
<td>68.61</td>
</tr>
<tr>
<td></td>
<td>R(1)</td>
<td>27.35</td>
<td>30.12</td>
<td>75.32</td>
</tr>
<tr>
<td></td>
<td>R(2)</td>
<td>24.98</td>
<td>27.33</td>
<td>54.65</td>
</tr>
<tr>
<td></td>
<td>R(3)</td>
<td>25.80</td>
<td>27.33</td>
<td>77.29</td>
</tr>
<tr>
<td>D = 80% S</td>
<td>C(1)</td>
<td>28.45</td>
<td>30.85</td>
<td>48.76</td>
</tr>
<tr>
<td></td>
<td>C(2)</td>
<td>27.08</td>
<td>30.56</td>
<td>68.61</td>
</tr>
<tr>
<td></td>
<td>R(1)</td>
<td>27.35</td>
<td>30.12</td>
<td>75.32</td>
</tr>
<tr>
<td></td>
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<td>24.98</td>
<td>27.33</td>
<td>54.65</td>
</tr>
<tr>
<td></td>
<td>R(3)</td>
<td>25.80</td>
<td>27.33</td>
<td>77.29</td>
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<td>D = 100% S</td>
<td>C(1)</td>
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<tr>
<td></td>
<td>R(1)</td>
<td>27.35</td>
<td>30.12</td>
<td>75.32</td>
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<tr>
<td></td>
<td>R(2)</td>
<td>24.98</td>
<td>27.33</td>
<td>54.65</td>
</tr>
<tr>
<td></td>
<td>R(3)</td>
<td>25.80</td>
<td>27.33</td>
<td>77.29</td>
</tr>
</tbody>
</table>

E. Do Market Price and Volatility of RT Depend Upon the Number of Capacity-Limited Links?

The previous investigation focused on the DA. Here, the focus is shifted to the RT in order to examine whether there is any difference between the two markets in terms of the influence of a line limit. The influence of the line limit on the average price and volatility of wholesale electricity in the RT market is summarized in Table VIII.

1) Finding 5: Most of findings related to the DA can be applied to the RT. There is a difference between Tables VI and VIII. The average prices in the RT are higher than those of the DA when the number of capacity-limited links is small. The difference in price volatilities of Tables VI and VIII.

2) Practical Implication 3: The results in Table VIII imply practically the importance of how to design the trading structure.
For example, California ISO had both DA and RT trading before the California electricity crisis (2000–2001). The DA trading was stopped after January 31, 2001. The current market provides only the RT trading. Was the decision correct? Of course, we know that a final reply to the policy inquiry needs a thorough investigation on trading structure. However, as summarized in Tables VI and VIII, the combined trading between the DA and RT outperforms the RT trading in terms of price stability (i.e., small volatility) (PJM, considered as the most successful ISO, operates under DA/RT trading).

F. Do Market Price and Volatility Depend on the Percentage Reduction of Current Line Limit?

Table IX summarizes how a percentage reduction from current line limits influences market price and volatility in the DA. Fig. 7 shows the current line limits assumed for the five transmission links of the five-zone market. A percentage reduction means that all the current line limits are reduced by a percentage. For example, 10% reduction implies that the capacity limits of the five links are reduced from the corresponding current line limits of 2500, 1000, 7000, 2500, and 3000 (MW) to 2250, 900, 6300, 2250, and 2700 (MW), respectively.

1) Finding 6: For a constant demand, there is a slight increasing trend in average DA market price along with the percentage reduction of current line limits. For example, 10% reduction produces market price of $72.40/MWH under $D = 50\%S$. The price increases to $76.32/MWH when the line limits reduces 50% from the current values. This observation can be applied to the other levels of demand from $D = 60\%S$ to $100\%S$. This indicates that the reduction of line limits does not have a major influence on an average price in the DA. Meanwhile, a major influence can be found in the volatility. There is a decreasing trend in the volatility along with the percentage reduction from current line limits. For example, the 10% reduction produces 89.38 in the volatility under $D = 90\%$. The volatility becomes 10.05 when the line limits are reduced to 50%.

2) Practical Implication 4: The bidding strategy of agents is constrained under a line limit on transmission if we set an upper limit on market price. The price limit on wholesale electricity is referred to “price cap” in regulatory economics, because the retail price of electricity is regulated, and hence, the wholesale price needs to be controlled in a specific price range. A typical case of the limited bidding strategy is found in $D = 100\%S$ where congestion occurs when the reduction of line limits becomes more than 40%. In this case, the price volatility of electricity is zero. The result implies that all agents do not have any bidding freedom except bidding the maximum bidding price under such an occurrence of congestion. Returning to the first assertion, we can restate it as follows: if there is no price cap, the learning speed of agents is influenced by market price of electricity. An agent becomes a slow learner if market changes drastically as found during the California electricity crisis. However, under the price cap, the agent determines his bidding price immediately (so, being a very quick learner with a short convergence time) because he does not have any bidding choice. Consequently, many utility firms may face bankruptcy, as found in the California electricity crisis period when the wholesale price was high and the retail price was controlled by a regulatory agency.

VII. CONCLUSION

This study incorporated a structural linkage between a transmission system and a power trading mechanism (for multiple zones) into an agent-based intelligent simulator. Then, we investigated how a line limit in transmission influences the wholesale market price of electricity.

The following implications were identified in this study
1) The learning speed of reinforcement learning depended upon a dynamic change of wholesale market price
2) A line limit increased the market price and volatility of electricity. The influence of the line limit depended upon both a market structure and a ratio of demand to supply.
3) The average price and volatility of electricity were influenced by the number of capacity-limited links.
4) There was no major difference between the DA and RT in terms of the influence of a line limit.
5) There was a slight increasing trend in the average DA/RT market price along with the percentage reduction of a current line limit.

As an extension of this study, we are interested in how investment on transmission lines influences a current price fluctuation of electricity in various ISOs. In this study, we have discussed that the investment in transmission lines among zones is important in terms of price reduction of electricity. In reality, investors are interested in the enhancement of transmission capacity only when an economic incentive is available to them. Considering various scenarios on transmission investment, a simulation-based investigation provides new evidence on current electricity restructuring plans. That is an important future research task of this study.

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