Multi-Agent Simulation of Generation Expansion in Electricity Markets

Audun Botterud, *Member IEEE*, Matthew R. Mahalik, Thomas D. Veselka,
Heon-Su Ryu, *Member IEEE*, and Ki-Won Sohn

***Abstract* — We present a new multi-agent model of generation expansion in electricity markets. The model simulates generation investment decisions of decentralized generating companies (GenCos) interacting in a complex, multidimensional environment. A probabilistic dispatch algorithm calculates prices and profits for new candidate units in different future states of the system. Uncertainties in future load, hydropower conditions, and competitors' actions are represented in a scenario tree, and decision analysis is used to identify the optimal expansion decision for each individual GenCo. We test the model using real data for the Korea power system under different assumptions about market design, market concentration, and GenCo's assumed expectations about their competitors' investment decisions.**

***Index Terms*—Electricity Markets, Generation Expansion, Agent-Based Modeling, Probabilistic Dispatch, Decision Analysis.**

I. Introduction

Traditional generation expansion planning in electrical power systems is usually based on centralized least-cost planning, subject to reliability constraints. However, the centralized least-cost planning approach does not reflect how investment decisions are made in today's electricity markets, where several generating companies (GenCos) are competing with each other, both in short-run operations and long-run investments. Some would argue that a well-functioning electricity market would converge toward the optimal expansion plan from a system's perspective in the long run. A competitive market should provide correct investment incentives through price signals in short- and long-term markets. Others, however, would contend that the independent and decentralized decision-making process in restructured electricity markets leads to suboptimal expansion plans. Several important factors, such as market power, limited information about competitors current and future actions, low demand-side participation, inadequate market design, and increased financial risk, cause the expansion decisions to deviate from the optimal plan.

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A. Botterud, M.R. Mahalik, and T.D. Veselka are with the Decision and Information Sciences Division, Argonne National Laboratory, 9700 S. Cass Avenue, Argonne, IL 60439, USA (e-mails: abotterud@anl.gov, mahalik@anl.gov, tdveselka@anl.gov).

H-S. Ryu and K-W. Sohn are with the Power Planning Department and the Market Operations Department, Korea Power Exchange, 167, Samseong-Dong, Gangnam-Gu, Seoul 135-791, Korea (e-mails: maxima@kpx.or.kr, kwson@kpx.or.kr).

It is still too early to judge all the long-term consequences of power industry restructuring from historical data, because of the large time horizon involved in capacity expansion. However, there is clearly a need to develop new modeling approaches to improve our understanding of the long-term price and investment dynamics in restructured electricity markets.

From a modeling point of view, the centralized least-cost expansion planning perspective is convenient, since one objective function can be used to optimize the entire system. The generation planning problem can then be solved using standard optimization methods, such as dynamic programming. Several models have been developed for traditional least-cost generation planning, e.g. the WASP model [1]. Modeling of generation investments in restructured electricity markets is a fairly new area of research. It is a challenge to model the strategic business interactions between competing GenCos, and at the same time include sufficient detail in the technical representation of the power system. In the literature we find some examples of generation planning models for restructured electricity markets based on game theory [2]. System dynamics [3], real options theory [4], and agent-based modeling [5] have also been applied to analyze GenCos' investment decisions.

In this paper we, present a novel model for analyzing generation expansion decisions in electricity markets. We use agent-based modeling to simulate the decentralized decision-making processes underlying GenCos' investment decisions. In the model, GenCos are represented as independent and decentralized agents interacting with each other in a complex, multidimensional environment. A convolution algorithm is used to simulate the market operation of current and future generation system configurations, taking into account thermal generators' forced outage rates and scheduled maintenance needs. A peak-shaving algorithm is used to represent hydropower dispatch. Uncertainties in future load growth, hydropower availability, and competitors' expected future investment decisions are represented with scenario trees. Finally, decision analysis is used to model each individual GenCo's investment decision. The model can simulate generation expansion decisions over a multiyear time period.

The paper has the following structure. First, we describe the algorithm of the new multi-agent generation expansion model. We then present results from testing of the model using realistic data for the power system in South Korea, where generation expansion decisions are simulated under a number of different assumptions about market structure and design. Conclusions and directions for future work are provided in the end.

II. Model Description

Argonne National Laboratory has spent several years developing an agent-based model for electricity markets. So far, the main focus of the Electricity Market Complex Adaptive Systems (EMCAS) model has been on short-term hourly simulations (see [6] and [7] for a description of EMCAS, with an example of an application in [8]). The development of the expansion model presented in this paper facilitates analysis of long-term investment aspects within the same multi-agent modeling framework.

A. Overview of the Expansion Model

The overall structure of the simulated decision making process is illustrated in Fig. 1. The model runs for a number of decision years. Within each decision year, each GenCo makes a forecast of future market conditions, in which it assesses potential investments in new generation capacity, taking into account the impact on the profitability of its own existing portfolio of plants. The actual system developments may deviate from the GenCos' expectations. Hence, as in the real markets, optimality is not guaranteed, neither from a GenCo nor from a system perspective. Currently, the GenCos consider investments only in thermal generation during the simulation. However, investments in other technologies, such as hydro- and wind-power, may be specified as external inputs. Plant retirements, regardless of the technology type, can also be specified as external inputs.

After GenCos have formulated expansion plans in a decision year, the plans are made publicly available. Based on an assumed technology-specific construction period, the new units come online in the system at a future date. For each decision year, the GenCos learn about the actions of their competitors through their announcements of new investment projects. The latest information about the current system, capacity retirements, and announced capacity additions are always taken into account by the GenCos in the assessment of new investment alternatives. However, information about expansion plans is not shared among the GenCos within the decision year. Hence, competitors' expansion decisions may be very different from what the individual GenCos originally forecasted.

A decision year simulation is performed to evaluate prices, GenCo profits, and generation system reliability within the decision year, based on the current system configuration. At the end of the decision year, expansion decisions of all GenCos are aggregated and the system is updated with the latest information about completed projects, retirements, and new announcements. Load growth rates are exogenous inputs to the model. There are two types of load growth rates: the first is the actual load growth rate, which is simulated for each decision year. This rate is unknown to the GenCos, until after a decision year has been simulated. The second rate is used by the GenCos in their forecasts and investment decision making and can consist of several scenarios, as explained below. It may deviate from the actual simulated load growth.

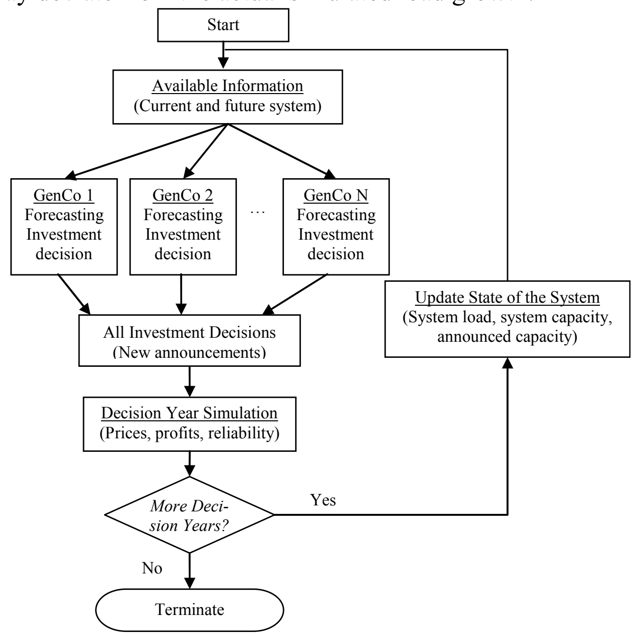

Fig. 1. Overview of simulated decision-making process in multi-agent expansion model.

Each GenCo uses the same general decision model. However, several of the parameters that go into the model, such as a GenCo's decision preferences, the probabilities of load and hydropower scenarios, and available investment alternatives may vary among the companies. At the same time, the GenCos will learn about the decisions of their competitors during the simulation. This will also contribute to differentiate the investment strategies applied by the various companies in the system. Another key component to investment decisions is that GenCos may have distinctly different portfolios of existing supply assets. One GenCo may estimate that it is profitable to build a certain new technology because it will have little or no impact on the profitability of its existing supply portfolio, while another GenCo may estimate that the same technology would not be profitable because it would have a large detrimental impact on its existing assets.

B. Uncertainty in Load Growth and Hydropower Generation

Load growth is an important driver for future prices and the need for capacity expansion in the system. There is usually considerable uncertainty regarding future load levels in the system. This uncertainty is represented in the model through scenarios describing the annual percentage change in the system load for each year in the forecast period. The hourly loads specified for the initial year are scaled for each forecast year depending on the load growth scenario.

In a system with considerable hydropower, the uncertain inflow of water into the system is also an important factor that must be considered. This uncertainty can be modeled by specifying a number of hydropower availability scenarios for all hydropower plants in the system. In the dispatch algorithm, the hydro generation is modeled with a peak-shaving logic, where the amount of peak-shaving within each week depends on the hydropower scenario. Other renewable and non-dispatchable resources (e.g. wind, biomass, waste) are represented with an hourly time series for generation that is subtracted from the forecasted loads.

C. Competitor Expectations

In a decision year, the GenCos know all the existing capacity in the system and what has been announced by their competitors in previous years. However, when forecasting prices and profits over the lifetime of a new unit, the GenCos also need to anticipate what investments their competitors are likely to make further into the future, i.e. beyond what has already been announced. To model future investments from other GenCos, we assume that each GenCo has an aggregate view of how much new capacity the rest of the market will add to the system over time. The representation of others' anticipated investments consists of the total installed capacity and the technology mix of the new competitor plants. Both of these characteristics are, of course, highly uncertain at the time a GenCo makes its investment decision. We, therefore, model the anticipated installed capacity and technology mix from others as scenarios. The first competition layer represents the anticipated total amount of new installed capacity that competitors will build over time. The second competition layer represents the technological composition of this new competitor capacity. The result is a scenario-tree structure used to represent uncertainties in load growth, hydropower conditions, and competitors' expansions (Fig. 2).

The new capacity built by others is linked to a GenCo-specific system reserve margin target that represents a GenCo's expectation about future system reserve margins. A GenCo assumes that the total investments from the competitors will cover a certain percentage of the required capacity needed to maintain the system reserve target. The competitor capacity type can be one of several specified candidate technologies. Hence, each GenCo can derive a complete competitor expansion plan based on the parameters described above for all scenarios in Fig. 2.

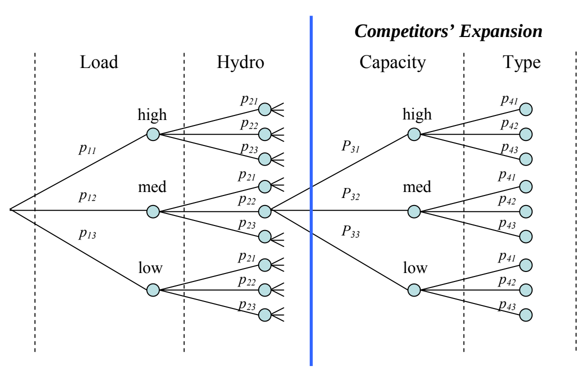

Fig. 2. Scenario tree for uncertainties in load growth, hydro conditions, and competitors' expectations.

To save computation time in the dispatch simulation we assume that all GenCos use the same scenario definitions for load growth and hydropower conditions. In the GenCos' representation of competitors' decisions, the capacity levels are defined individually for each GenCo, as explained above, whereas the definition of capacity types is the same for all GenCos. However, the probabilities are specified individually for each GenCo over all four layers in the scenario tree. The scenario probabilities are currently exogenous inputs to the model and kept constant during the simulation. However, in future versions the idea is that the GenCos can learn and update these probabilities during the simulation.

Prices and profits must be calculated for all GenCos' units over all leaves in the scenario tree. Computational efficiency is, therefore, of major importance in the dispatch algorithm, which is outlined below.

D. Probabilistic Dispatch: Prices, Profits, Reliability

A probabilistic dispatch algorithm based on the traditional Baleriaux-Booth method [9] is used to model forced outages in thermal units and their impact on prices and reliability for a given system configuration. An equivalent load, L_e, represents the load that a unit will serve accounting for outages of units that are lower in the merit order dispatch. L_e can be defined as:

$$L_e = L_s + L_r \tag{1}$$

where

L_s	original system load	[MW]
L_r	forced (random) component of unit outages	[MW]

The cumulative probability distribution of the equivalent load is found by convoluting each thermal unit's forced outages into the original system load. This is done in merit order, based on the units' marginal production cost. A single load level is evaluated at a time. Hence, the cumulative distribution for the initial load is a vertical line (Fig. 3). As units are convoluted into this curve, the resulting equivalent load curve is transformed into one that has an upper elongated tail. The resulting cumulative probability distribution function for L_e is calculated recursively, based on (2). The probability of a thermal unit being the marginal producer in the system is also determined. We assume that all thermal units bid their marginal production cost. Therefore, the price probability is given by (3). The probability of having energy not served (ENS) and, therefore, price being equal to a regulatory price cap, P_{CAP}, is given by (4). An illustration of the convolution process and the price distribution calculation for a given load level, L_s, in a simple system with two units of equal size is shown in Fig. 3.

$$F_n(L_e) = p_n F_{n-1}(L_e) + q_n F_{n-1}(L_e - C_n) \tag{2}$$

$$f(MC_n) = F_{n-1}(TC_{n-1}) - F_n(TC_n) \tag{3}$$

$$f(P_{CAP}) = F_N(TC_N) \tag{4}$$

where

$F_n(L_e)$ cumulative probability distribution for L_e, $F_0(L_e \leq L_s) = 1$, $F_0(L_e > L_s) = 0$

$f(MC_n)$ probability price equals marg. cost unit n, MC_n

$f(P_{CAP})$	probability price equals price cap, P_{CAP}	
C_n	capacity of generating unit n, n = 1..N	[MW]
TC_n	sum capacity of generating units 1.. n	[MW]
p_n	probability unit n in operation	
q_n	probability unit n on forced outage (p_n+q_n=1)	

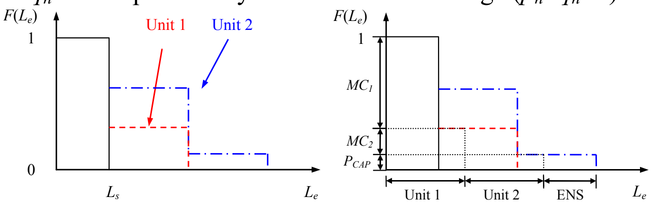

Fig. 3. Calculation of cumulative distribution for equivalent load (left), and price distribution (right) for a given load level, L_s. ENS = Energy Not Served.

Probabilistic convolution is done for each month. Planned maintenance of the thermal units is taken into account. A monthly maintenance scheduling routine is used, which minimizes the maximum monthly loss of load probability in each year. Hydropower and non-dispatchable generation is subtracted from the original hourly loads within the month, using a peak-shaving algorithm for hydro power. Price distributions are calculated for a sample of the resulting thermal loads, and the results are aggregated into a monthly price distribution. Note that it is necessary to perform the recursive convolution only for the maximum thermal load in the month over all load/hydro scenarios. The resulting convolution curves are stored in tables with small discrete load steps. The price distribution for lower load levels can easily be derived from the probabilities stored in the convolution table for the maximum thermal load. Monthly price distributions are calculated for each load/hydropower scenario throughout the planning period, taking into account the monthly maintenance plan. However, the underlying convolution tables need to be updated only for each new forecast period (i.e. when the portfolio of thermal plants in the system changes, due to either retirements or new announced capacity). Furthermore, all GenCos use the same convolution tables when evaluating profitability of new units. This greatly improves the computational efficiency of the model.

The aggregated monthly price distributions are used to calculate the profitability of new candidate units. In addition, the impact of a new unit on the profitability of a GenCo's existing thermal and hydropower units due to potential reduction in prices is also estimated. The resulting cost and revenues for a new candidate plant, discounted over all months in the payback period and calculated for all scenarios in the scenario tree (Fig. 2), are used as input to the GenCo's investment decision.

The unannounced capacity in the GenCos' expectations about competitors' future investments is not included in the convolution procedure described above, as this information is GenCo specific. However, an approximation is made to take into account how this capacity influences prices and candidate unit profit in the different competitor expectation scenarios for each GenCo. A GenCo's own unannounced new capacity is handled in a similar manner within each decision year.

E. Decision Analysis

Decision analysis is used to identify the preferred investment decision for each individual GenCo. Multi-attribute utility theory (MAUT) is used to calculate the expected utility from all possible investment decisions, including not investing at all. The optimal decision according to MAUT is to choose the alternative with the highest expected utility. The underlying assumption is that a decision maker's preferences can be quantified in terms of a multi-attribute utility function. The utility function takes into account the decision maker's risk preferences and the trade-offs between different objectives. The theoretical background for MAUT is thoroughly described by Keeney and Raiffa in [10].

We use the additive form of the multi-attribute utility function, i.e., the total utility for an alternative equals the weighted sum of the single attribute utilities, as shown in (5). An exponential form is used for the single-attribute utility functions, as shown in (6). The corresponding risk parameters indicate risk preferences for the individual attributes. If β is zero, the decision maker is risk-neutral. A negative β means risk aversion, whereas a positive β means a risk-seeking attitude. The upper and lower limits of each attribute refer to the maximum and minimum values considering all candidate technologies.

The trade-off weights and the risk parameters are specified as input for each GenCo and can be used to represent different preferences among the market participants.

$$u(\boldsymbol{x}) = \sum_{i=1}^{m} k_i \cdot u_i(x_i) \tag{5}$$

$$u_i(x_i) = 1/(1-e^{\beta_i}) \cdot \left\{1 - e^{\beta_i (x_i - \underline{x}_i)/(\overline{x}_i - \underline{x}_i)}\right\} \tag{6}$$

where

$u(\boldsymbol{x})$	total utility for attribute set $\boldsymbol{x} = x_1, x_2, ..., x_m$
$u_i(x_i)$	utility for single attribute, i = 1,2, ..., m
k_i	trade-off weight, attribute i
β_i	risk parameter, attribute i
$\overline{x}_i$	upper limit, attribute i
$\underline{x}_i$	lower limit, attribute i

Currently, three attributes can be taken into account in the model: 1) Profit over unit payback period, i.e. (discounted revenue) – (discounted cost); 2) Profit ratio over unit payback period, i.e. (discounted profit)/(discounted cost); and 3) Market share, measured in terms of capacity at a certain time in the future. These attributes are calculated for all the leaves in the scenario tree (Fig. 2). The expected utility for an alternative is then calculated over all leaf scenarios based on the probabilities in the tree.

In each decision year, a GenCo must decide how many units to build of each candidate unit technology type. The number of possible alternatives can therefore become very high. To reduce the discrete search space, we limit the GenCo to choose only one plant at a time. In the algorithm, the GenCo therefore calculates the expected utility for one unit of all its candidate technologies. The unit with the highest expected utility is chosen. The process is repeated with plants already selected added to the GenCo's fleet of existing units. The iterative selection process continues within the same decision year until the GenCo's choice is to not build more plants, or until an imposed constraint on the GenCo's annual capacity expansion is reached.

F. Flowchart of Expansion Code

A flowchart describing the main parts of the multi-agent expansion code is given in Fig. 4. Note that in the decision year loop, steps 3–6 are done only once in each decision year, and the results are used by all GenCos. In contrast, the calculation of competitor expectations (step 2) and candidate unit evaluation and decision analysis (step 7) are done individually for each GenCo.

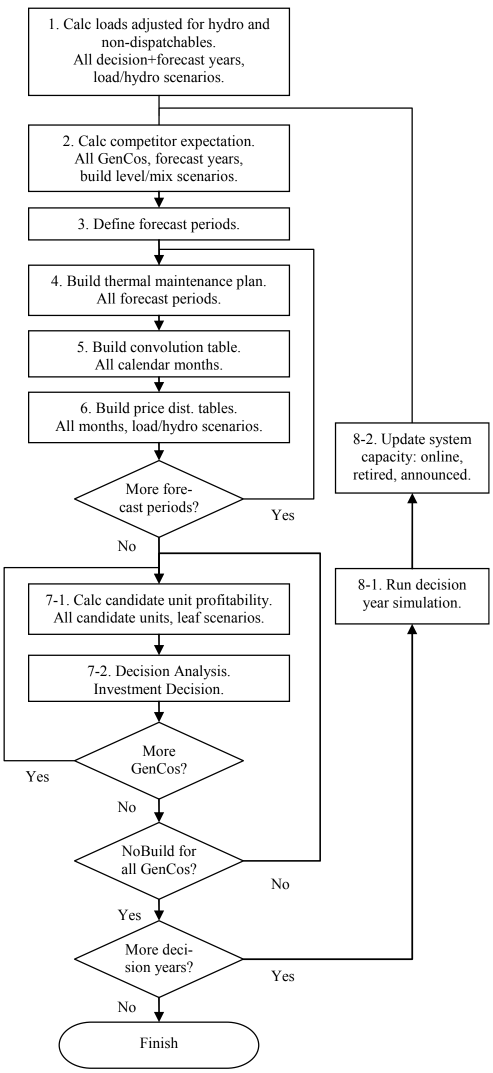

Fig. 4. Flowchart of multi-agent expansion algorithm.

III. CASE STUDY: KOREA POWER SYSTEM

We have tested the new expansion model in collaboration with Korea Power Exchange (KPX), using real data for the Korea power system. A selection of results is presented below. Note that the only purpose of the case study was to test the new EMCAS expansion model. None of the results are used for actual planning purposes by KPX.

A. Assumptions for Korea Power System

The technical specifications for the power system and the load forecast assumptions are based on the 3rd Basic Plan for Korea Long-Term Power Supply and Demand [11]. A 15 year simulation period is used, starting from 2006. Table 1 shows the expected long-term load growth for the Korea power system within this period. The peak load is expected to be gradually saturated in the far future. In the expansion model, we use the growth rates in Table 1 in the decision year simulations, whereas the GenCos' forecasted growth rates, which are used as input to their price and profit projections, are set to 2.5% until 2014 and 2.0% afterwards.

TABLE 1
LONG-TERM LOAD FORECAST FOR KOREA POWER SYSTEM

Year	Peak(MW)	Growth Rate
'05	54,631	-
'06	56,681	3.8%
'08	61,132	3.5%
'10	64,605	2.6%
'12	67,120	1.8%
'14	68,832	1.1%
'16	70,049	0.8%
'18	71,025	0.7%
'20	71,809	0.6%

The installed capacity in the Korea power system in 2005 was about 62.7GW. An additional 20.8GW is under planning and construction and will be built by 2020 (Table 2). Nuclear and coal capacity each account for about 30% of total capacity. About 20 % of capacity consists of Natural Gas Combined Cycle (NGCC) plants. There is also a small amount of hydropower generation and other renewable generation in the system. The capacity in Table 2 comprises a total of 127 units, which are all represented individually in the input data.

TABLE 2
EXISTING CAPACITY AND UNITS UNDER CONSTRUCTION [MW, %]

Technology	Existing Cap. (as of 2005)	Under Construction (until 2020)	Retiring Cap.	Share (%)
Nuclear	17,716	6,800	-	31.7
Coal	17,965	6,540	1,525	29.7
NGCC	16,449	1,500	1,537	21.2
Oil	4,662	200	2,643	2.9
Hydro	3,829	2,400	-	8.0
COGEN	1,382	1,983	-	4.3
Renewable	210	1,433	-	2.1
Other.	52	9	-	0.1
Sum	62,265	20,865	5,705	100
TOTAL SUM	77,425			

There are many existing GenCos in the Korea power market. As shown in Table 3, the share of the nuclear company, KHNP, is about 32%, and the share of the five major coal companies is about 53% of the installed capacity. The capacity shares of the other existing companies are small. For simplicity, we use an aggregate representation for the small companies. In addition to the existing companies, we also include two new GenCos (new entrants) in the expansion simulations.

We used five candidate units (Table 4), whose bid prices are based on the production cost. It is assumed that the nuclear company can build only Nuclear 1400. The five coal companies can build both Coal (870, 1000) and NGCC (500, 700). The NGCC companies and the new entrants can build NGCC (500, 700) only. The technical data of candidate units is shown in Table 4. Nuclear units have the highest capital and lowest operating cost, and vice versa for the NGCC unit. The expected forced outage rates (EFOR) are around 5% for all candidate units. A 7.5 % discount rate was used for all candidate units and GenCos.

TABLE 3
EXISTING COMPANIES AND THEIR CAPACITY SHARE (AS OF 2020)

Entrants	Name	Resource	#of units	Share(%)
Existing GenCos	KHNP	Nuclear & Hydro	26	32.4
	NADO	Coal & NGCC & PS	15	12.4
	JUBU	Coal & NGCC & PS	14	8.4
	SEBU	Coal & NGCC & PS	18	10.0
	NABU	Coal & NGCC & PS	19	10.7
	DOSE	Coal & NGCC & PS	20	11.5
	PSCP	NGCC	4	2.3
	GSEP	NGCC	2	1.3
	GSPW	NGCC	2	1.2
	MYUC	NGCC	1	0.7
	KPWR	NGCC	2	1.3
	SUJA	Hydro	1	1.3
	COGEN	NGCC & Oil	1	4.3
	Renewable	Wind, LFG, etc.	1	2.1
	Others	Others	1	0.1
New Entrants	DARM	NGCC	0	0
	SKES	NGCC	0	0

TABLE 4
CANDIDATE UNITS CHARACTERISTICS. EXCHANGE RATE: 1 KWON ≈1$.

Technology	Fuel Cost (kWon/Gcal)	Payback Period(year)	Construction Period (Year)
NGCC 500	35.4	20	3
NGCC 700	35.4	20	3
Coal 870	9.5	25	7
Coal 1000	9.5	25	7
Nuclear 1400	1.4	30	10

We used a simplified scenario tree structure in the simulations presented here, with only one load growth scenario and one hydropower scenario (based on actual hydropower data for 2005). For the competitor expectations, we used one build level scenario, and three build type scenarios (NGCC 500, NGCC 700, and Coal 1000 with equal probability for each type). Other simulation parameters are summarized in Table 5 (base case). The GenCo's Own Build Limit is a constraint on how much each GenCo can build within each decision year, as a percentage of the total capacity required in the system to meet the expected reserve margin.

TABLE 5
SIMULATION PARAMETERS

Parameter	GenCo		
	NGCC	Coal	Nuclear
Reserve Margin Parameter	30%	30%	30%
Genco's Own Build Limit	12%	12%	12%
Competitor Expansion	100%	95%	55%
Decision Analysis Attribute	Profit Ratio	Profit Ratio	Profit Ratio
Risk Preference	Neutral	Neutral	Neutral

B. Case Study Simulations and Results

We first simulated a base scenario, where the input parameters, as shown in Table 5, were calibrated to obtain results similar to a reference expansion plan for Korea from the WASP model [11]. A number of additional scenarios were simulated, where results were compared to the base case. Below we present results from sensitivity analyses of the energy market price cap, the GenCo's expectation about competitors' future expansion decisions, and the effect having no any new entrants investing in new capacity.

1) Base Case

The simulated generation capacity expansion in the base case is shown in Fig. 5. We can see that the GenCos invest in the NGCC 700, Coal 1000, and Nuclear 1400 technologies. The two new entrants (SKES, DARM) build most of the new NGCC capacity. JUBU is the GenCo with most coal expansion, whereas KHNP builds two nuclear plants, which come online toward the end of the simulation period. From the simulated prices and reserve margin (Fig. 6), we see that the price gradually decreases and stabilizes around 60 kWon/MWh, whereas the reserve margin grows towards a level of approximately 20%.

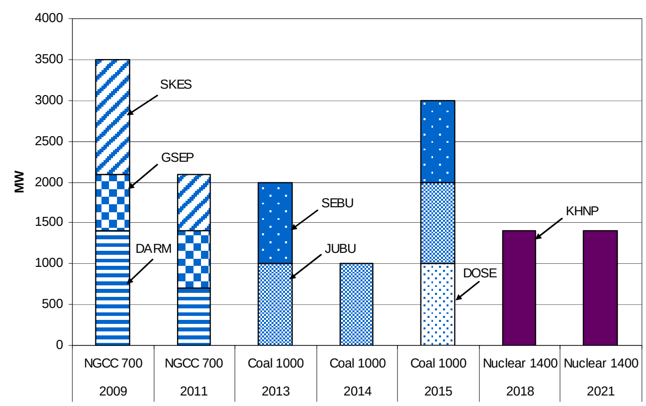

Fig. 5. Base case expansion by technology, GenCo and online year.

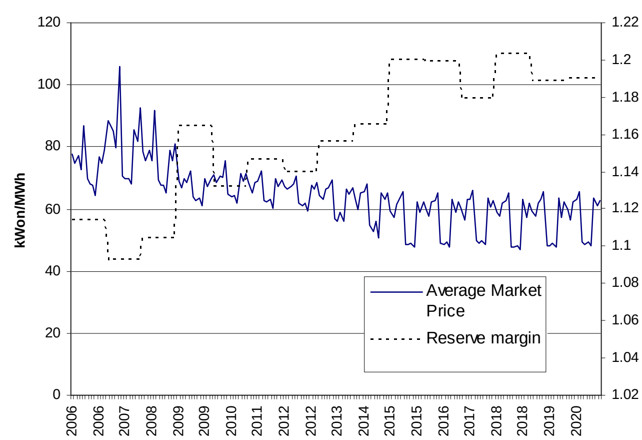

Fig. 6. Average monthly market price and annual reserve margin. Base case.

2) Sensitivity to Lower Energy Price Cap

The level of the energy price cap is very important for the incentive to invest in new generation capacity, since it determines the price and GenCos' income during periods with shortage of supply. Ideally, the price cap should be set to a high value equal to the value of lost load. However, regulators tend to set a lower price cap in electricity markets to avoid very high prices. In the base case we used a price cap of 999 kWon/MWh. We repeated the simulations with lower price caps to analyze the effect on expansion decisions, prices, and system reliability. Table 6 shows that a lower price cap reduces the investments in new generation capacity. This is because GenCos are less willing to invest in new generation capacity due to lower expected profitability. Investments in new NGCC plants seem to be most sensitive to the price cap, probably because this technology is dispatched less than coal and nuclear plants and is, therefore, more dependent on the profit during hours of scarcity. Furthermore, the investment decisions of new entrants are apparently more sensitive to the price cap than are those of the existing GenCos.

TABLE 6
EXPANSION BY GENCO FOR DIFFERENT PRICE CAPS

Genco	Base case NG7/ CO10/ NU14	Price cap = 750 NG7/ CO10/ NU14	Price cap = 500 NG7/ CO10/ NU14	Price cap = 300 NG7/ CO10/ NU14
New Entrants	6 / 0 / 0	4 / 0 / 0	4 / 0 / 0	0 / 0 / 0
Existing NGCC	2 / 0 / 0	2 / 0 / 0	1 / 0 / 0	0 / 0 / 0
Existing Coal	0 / 6 / 0	0 / 6 / 0	0 / 4 / 0	0 / 1 / 0
Existing Nuclear	0 / 0 / 2	0 / 0 / 2	0 / 0 / 2	0 / 0 / 1
Sum(MW)	14,400	13,000	10,300	2,400

Fig. 7 shows that simulated prices go up as a function of lower price cap, particularly with a price cap as low as 300 kWon/MWh. Hence, the simulations show that a regulatory policy of setting a low price cap, which aims to protect the end-users from high prices in the short-run may, in fact, lead to increasing prices in the long run because of a lower rate of investments. The simulated reserve margin also goes down, and in the 300 kWon/MWh scenario it actually drops to a level close to zero. The results illustrate the importance of designing a market with adequate incentives for investments in new generation capacity. An interesting extension of the analysis would be to consider the effect on investments from different capacity adequacy policies, such as capacity markets.

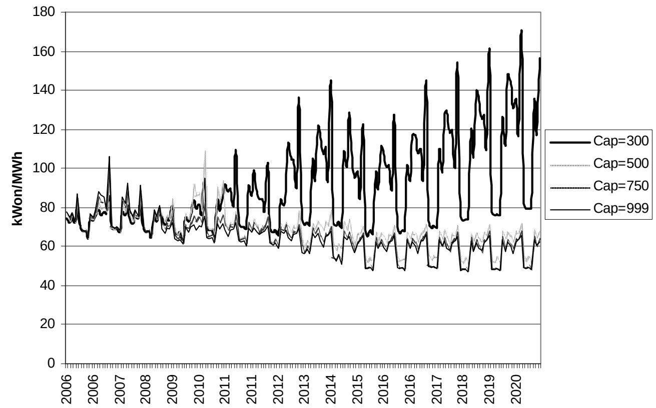

Fig. 7. Average monthly market price for different energy price caps.

3) Sensitivity to Competitor Expansion Expectations

The GenCos' expectations about competitors' expansion plans are important for their investment decisions, as outlined in Section II.C. To study the representation of competitor expectations in more detail, we changed the competitor unannounced expansion level parameters for the six coal GenCos. It was set to 95% for these GenCos in the base case, i.e. each GenCo expects that future unannounced expansion from all competitors will add up to 95% of what is required to meet the expected system reserve margin of 30% (Table 5).

When the competitor expansion parameter for coal GenCos is reduced to 90%, the level of investment for these companies increases compared to the base case (Fig. 8). This is because the coal GenCos now forecast lower rates of investment from their competitors, which in turn means that their projections of future prices and profits from ther own units increase. In contrast, when the competitor expansion expectation is increased to 100%, the coal GenCos build less capacity (Fig. 9). In fact, GenCo NADO and DOSE, whose existing capacities are higher than those of other coal GenCos, will build no new units. At the same time, other GenCos invest in more NGCC capacity than in the base case, which makes up for parts of the reduction in the new coal capacity.

The simulated prices and reserve margins are also affected by the changes in the competitor expectation parameter. Prices go down and the reserve margin goes up compared to the base case in the 90 % competitor expectation scenario, and vice versa for the 100% scenario.

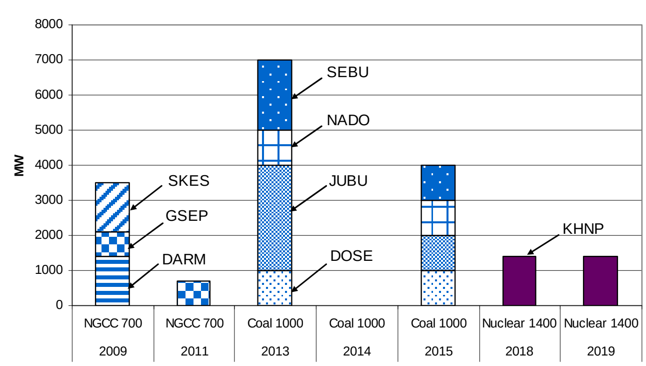

Fig. 8. Expansion by technology and GenCo with coal GencCs' competitor expansion parameter reduced to 90%.

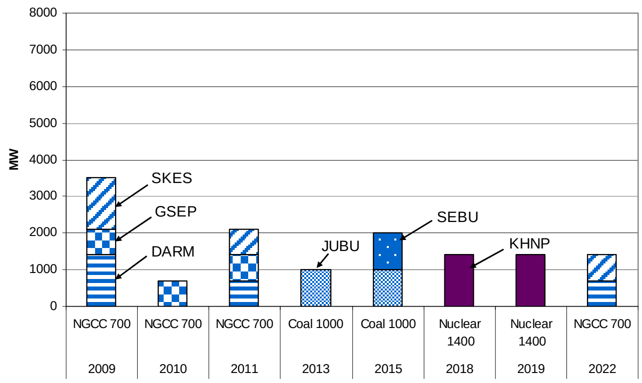

Fig. 9. Expansion by technology and GenCo with coal GenCos' competitor expansion parameter increased to 100%.

4) No New Entrants

Finally, we looked at the effect of removing the two new entrants (DARM and SKES) from the expansion simulation. It turned out that this had a profound effect on the results; the total level of new investments decreased dramatically. No new NGCC plants were built (i.e., a reduction from eight to zero NGCC 700 plants compared to the base case). At the same time, the number of new Coal 1000 plants dropped from six to four. KHNP still builds the two new nuclear plants, although they come online one and two years later than in the base case.

The reduction in new capacity leads to a major increase in prices, as shown in Fig. 10. The results from this scenario serve to illustrate the important role of new entrants in electricity markets. The new entrants can clearly lower the thresholds for investment and thereby contribute to keep prices at a competitive level.

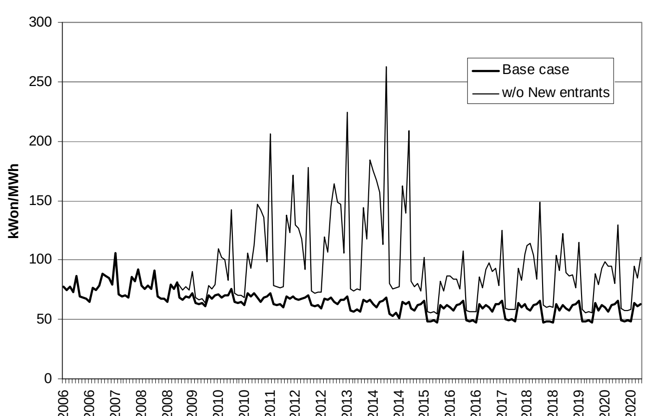

Fig. 10. Simulated average market price in scenario without new entrants.

IV. Conclusion

The multi-agent expansion model presented in this paper simulates the complex interaction between decentralized and profit-maximizing GenCos in restructured electricity markets. The presented results from test simulations of the Korea power system shows that the model can provide important insights into the long-term development of generation investments, prices, and reliability in real-world systems. Important issues regarding market design, GenCo decision preferences, and market concentration, can be analyzed. Such results can not be obtained with traditional generation expansion models.

We see a number of interesting extensions to the model, including: 1) Revision of the probabilistic dispatch logic to account for strategic bidding; 2) Simulate the effect of different capacity adequacy policies, such as installed capacity markets; 3) Model transmission constraints and location of new generating plants; and 4) Introduce more advanced learning and adaptation, so that GenCos adjust their forecast of the future depending on what they learn during the simulation.

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VI. Biographies

Audun Botterud (M'41576374) was born in Stange, Norway, on June 17, 1974. He received M.Sc. in Industrial Engineering (1997) and Ph.D. in Electrical Power Engineering (2003), both from the Norwegian University of Science and Technology. He was working at SINTEF Energy Research, Trondheim, Norway, from 1998 to 2000. In 2005 he joined Center for Energy, Environmental, and Economic Systems Analysis (CEEESA) at Argonne National Laboratory (ANL). His research interests include power system planning and economics, stochastic optimization, decision analysis, and agent-based modeling.

Matthew Mahalik is a software engineer who has been with CEEESA at ANL since 2000. Much of his work has focused on developing the GTMax and EMCAS models. Mr. Mahalik is proficient in the leading software languages, and is also proficient in the development of linear, non-linear, and integer programs that are frequently used for CEEESA models. Much of his recent focus was on agent-based modeling techniques and hydropower modeling in support of CEEESA's EMCAS software. Mr. Mahalik holds a degree in Computer Science from the University of St. Francis.

Thomas D. Veselka is an Energy Systems Engineer in CEEESA at ANL. He has provided technical support and managed projects related to electric utility systems and the environment for over 20 years. His work includes extensive hydropower systems analyses as related to power markets.

Heon-Su Ryu (M'40209135) was born in Korea, on June 03, 1969. He received B.S, M.S., and Ph.D. degrees in Electrical Engineering from Yonsei University, Korea, in 1992, 1996, and 2002, respectively. In 2002, he joined the Korea Power Exchange, and is now with the Power Planning Department. Dr. Ryu is a member of the IEEE Power Engineering Society. His interests are in the areas of generation and transmission planning and power system stability analysis.

Ki-Won Sohn was born in Korea, on April 24, 1975. He received B.S degree in Electrical Engineering from Dongguk University, Korea, in 1999. In 2001 he joined the Korea Power Exchange, and is now with Market Operation Department.