Microgrid Generation Expansion Planning Using Agent-Based Simulation

Yanyi He, *Student Member, IEEE*, and Ratnesh Sharma, *Member, IEEE*

***Abstract*-- This paper explores new application of agent-based simulation in the novel framework of exploitation of renewable resources in microgrids. A bi-layer (operational layer and investment layer) multi-agent model is proposed for microgrid operators (MGOs) to maximize their long-term planning profits in an energy market, which is built and regulated by the utility company (UC) in order to alleviate UC's environmental obligations. UC tries to maximize its revenue and minimize payment to satisfy demand for renewable generation. The results of investment plans with peaked choice probabilities in the investment layers are treated as the best decisions of MGOs' expansion planning in the evolutionary game. An example with twenty years planning horizon is given to illustrate the proposed model and market mechanism.**

***Index Terms*—Agent-based simulation, microgrid, generation expansion, energy market, the utility company, reinforcement learning algorithm (RLA).**

I. Introduction

THE power industry has experienced restructuring in recent decades due to economic and technical reasons. This had led to emergence of microgrids as a viable building block of next generation infrastructure. Microgrid is a group of coordinated generators and loads, operates as a single entity in the distribution systems. Microgrids are an important building block of next generation smart grid providing renewable generation and other crucial grid support services to the grid operator. Grid connected microgrid can trade arbitrary energy with the grid. The role microgrids play in the distribution systems shifts from dependent to inter-dependent with the grid, as the emphasis of renewable energy technologies [5]. For example, microgrids could leverage the loss in the distribution systems, and can help to reduce the carbon emissions [6].

Currently, many environmental policies are focused on the transmission power systems, for example, generation companies or the load serving entities. The utility company, which is more like a load serving entity, has an obligation to reach some environmental goals. If microgrid is a renewable source connected to the grid, the utility company could initialize an economic mechanism to utilize the renewable energy in microgrid to alleviate its environmental requirement. The most straightforward approach is to start up a market to trade the renewable energy with microgrid operators. Contribution of small-scaled microgrid is subtle in the distribution systems, but there is strength in numbers. Individual contributions of microgrids can complement each other to make a significant contribution, facilitating the utility company to comply with environmental regulations, thus accelerating the process towards energy systems' sustainability [1]. The market power of microgrids lies in the level of source and demand of the utility company. Greater market power comes with greater opportunities of profit. Great profit opportunities induce the competition in the market ultimately.

The modeling of the competition with perfect information is usually analyzed with game theory [2]. In [4], the authors applied game theory to study the interactions of the utility company and microgrid operators. However, in the first place, due to the computational complexity, it is hard to solve long-term planning problem with complementarity constraints; in the next place, perfect information scenario is rarely realized in practice, which means perfect game approach is not practical in implementations of real world problems.

Agent-based modeling and simulation (ABMS) is a new approach with rising popularity [3]. Its application broadly ranges from various disciplines, including physics, stock market, social networks, or electrical engineering. ABMS can decouple complex systems into individual interdependent agents with adaptive behaviors. The agents can inherit the complexity by performing adaptive behaviors as the environment evolves. ABMS applications in electrical engineering take place in both transmission and distribution systems.

In the transmission systems, ABMS is widely used to study the players' complex bidding behaviors in the wholesale market [10-12, 15]. Each generator or load serving entity maximizes their profit or welfare through user-defined learning algorithm in the bidding market. ABMS can also be employed in planning problems. Self-concerned generation companies compete to maximize their profit in the planning horizon. Generation company or generator can be modeled as an agents like [7,8]. ABMS applications in microgrid planning or expansion problems focus on single microgrid [9], where microgrid is relatively independent with others. In [14], the authors looked for the optimal generator or storage sizing of a single microgrid. Other ABMS applications in microgrids emphasize on the operations or control of the microgrids. Few peer works on the expansion of competing microgrids exist.

The goal of our work is to propose an agent-based simulation framework for the microgrid operators (MGOs) to

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Yanyi He is a Ph.D candidate at Iowa State University, Ames, IA, 50010 USA (e-mail: heyanyi@iastate.edu)

Ratnesh Sharma is the department head of Energy Management Department at NEC Laboratories America, Cupertino, CA, 95014 USA (e-mail: ratnesh@nec-labs.com)

maximize their long-term planning profits in an energy arbitrary market, which is built and regulated by the utility company (UC) in order to alleviate its environmental obligations. The framework is showed in Fig. 1. The utility company is subject to the environmental regulations and wants to utilize aggregated renewable resources in the connected microgrid to accomplish the environmental regulations. The utility company builds a renewable energy market where microgrid operators could sell the profitable renewable energy to the utility company. If the electricity payment in the renewable market plays a role of subsidy or incentives, microgrid operators would perceive a business opportunities and invest in more renewable generation.

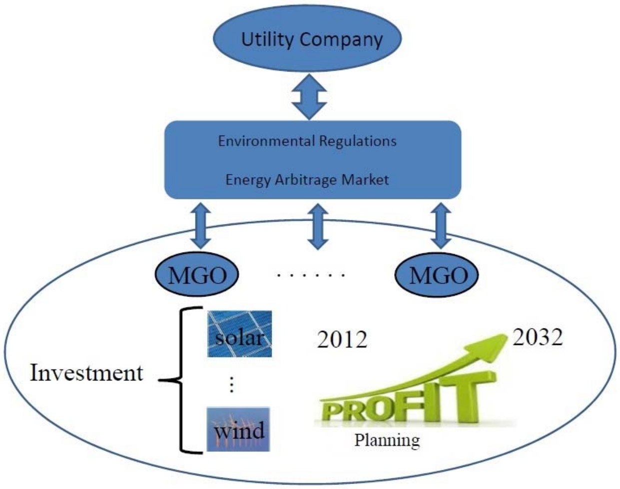

Fig. 1. Energy Market Framework

The rest of the report is organized as follows: Section II describes the detailed framework of our problem; Section III is the introduction of our case study; Section IV and V summarizes the results and provides some discussions. Section VI concludes the paper.

II. Framework

The market stems from the renewable demand of the utility company, and is regulated by the utility company. The market is enclosed with microgrid operators and the utility company.

A. The utility company

The utility company participates in the environmental regulations. It starts a new renewable energy market, wherein it provides incentives to buy renewable energy to reduce its environmental regulation burden. The utility company allows the microgrid operators to submit their bids, and it compares bids from microgrid operators and selects the cheapest ones to reach the predefined renewable demand subject to the payment budget. The predefined renewable demand and payment budget is confidential to microgrid operators.

In order to avoid the emission leakage while microgrids supply the renewable energy, microgrids which participate in the market must be subject to the emission cap. The utility company only accepts bids from qualified renewable generation. Each microgrid can only supply one bid for one type of renewable resources. The bid contains type of renewable resource, price and quantity. The utility company will clear the market at the beginning of a day.

The market clearing problem is formulated in (1) to (5).

$$\min \quad \sum_{i,g} P_{i,g}^{m} q_{i,g}^{m} + P^{vd} q^{v} \tag{1}$$

$$\text{s.t} \quad q_{i,g}^{m} \le Q_{i,g}^{m} \tag{2}$$

$$\sum_{i,g \subset \text{clean}} q_{i,g}^{m} = Q^{u} - q^{v} \tag{3}$$

$$\sum_{i,g} P_{i,g}^{m} q_{i,g}^{m} \le P^{u} \tag{4}$$

$$q_{i,g}^{m}, q^{v} \ge 0 \tag{5}$$

where Q^u and P^u are the utility company's bid quantity and payment; $Q_{i,g}^{m}$ and $P_{i,g}^{m}$ are microgrid operator i's bid quantity and price of generator type g; P^{vd} is the virtual penalty of unsatisfied renewable demand; $q_{i,g}^{m}$ is the market cleared quantity of generator type g for microgrid operator i. Equation (1) is the cost minimization objective. Equation (3) is the supply and demand balance constraint. Equation (2) and (4) are the renewable electricity quantity and total payment's constraints, respectively. Equation (5) is variables' non-negativities.

The capability of the utility's market regulation is quantitatively measured via a utility function. The utility of the utility company is defined with respect to the deviation of the utility company's estimated demand and payment: $\exp(\frac{-q^{v}}{Q^{u}})\exp(\frac{\sum_{i,g} P_{i,g}^{m} q_{i,g}^{m} - P^{u}}{P^{u}})$. The maximal utility value is 1.0. The higher the utility value is, the more capably of the utility company regulate the market.

B. Microgrid Operators

Microgrid operators intend to optimize their long-term planning profit under the renewable market regulations. Microgrid operators conduct two major tasks during the planning horizon. Firstly of all, microgrid operators serve the local loads with minimal cost and ensure the electricity supply (heat supply is not considered in this framework). Secondly, microgrid operators explore the business opportunities in the market. There are growing demands for clean energy, such biomass, wind, thermal energy and so on. The utility company is willing to pay relatively high electricity price for clean energy, if microgrids participate in some environmental regulations. If the electricity price is greater than an investment threshold, microgrid operators find profitable to invest in excess clean energy and sell to the utility company. The investment threshold is determined by the investment cost, incentives and environmental awareness. Microgrid operators have no idea of the incentives unless they are in the markets. Microgrid operators would have a group of candidate investment plans in advance based on their own perceptions of the market. Investment decisions include both renewable and non-renewable investment. Those investment plans are selected based on estimation of other microgrid operators' investment and the utility company demand. Each investment plan has different return in the renewable market. The return also depends on the decision making of other market players. The return of the investment plans is computed via the bidding and operation optimization in the renewable market. It is because even if the investment plans are all given by microgrid operators, the profits of microgrids are not determined yet. The profits depend on the learning of the microgrid operators in the renewable bidding market as well. Hence the bidding process is an agent-based simulation itself.

We assume microgrid operator knows who are in the market, but do not know their database, like residential electricity demand, existing generator etc. Microgrid operators can buy/sell electricity from/to the utility company. At the beginning of each day, microgrid operators submit their bids to the utility company. Bids contain types, maximal quantities and prices of energy.

After market clearance, microgrid operators will run its daily profit optimization problem. Unsatisfied supply to the utility company is subject to penalty, which is 1.2 times of the bid price. Purchased energy from the grid does not require specific types. Sold energy to the utility company can only be renewable energy.

MGO's profit maximization problem is formulated as:

$$\begin{aligned}
\max \quad & -\sum\nolimits_h [pum \cdot eu_h + OCS \cdot (ec_h + ed_h)] \\
& + \sum\nolimits_g OC_g^u \cdot (X_g^c - 1.2 x_g^{uc}) - \sum\nolimits_{h,g} OC_g^e \cdot (x_{h,g} + xu_{h,g}) && (6) \\
\text{s.t.} \quad & x_{h,g} + xu_{h,g} \le \eta_{h,g} \cdot X_g^{\max} && (7) \\
& s_h = s_{(h-1)} + \rho^{sc} \cdot ec_h - ed_h / \rho^{sd} && (8) \\
& ed_h \le \rho^{sd} \cdot s_{(h-1)} && (9) \\
& s_h \le s^{\max} && (10) \\
& \sum\nolimits_h x_{h,g} - (ec_h - ed_h) = LE_h - eu_h && (11) \\
& \sum\nolimits_{h,g} \chi_g \cdot (x_{h,g} + xu_{h,g}) \le E^{\mathrm{co2}} && (12) \\
& \sum\nolimits_h xu_{h,g} = X_g^c - x_g^{uc} && (13) \\
& x, xu, ec, ed, x_g^{uc}, s, eu \ge 0 && (14)
\end{aligned}$$

where parameters pum, OCS, OC_g^u, OC_g^e, X_g^c, $\eta_{h,g}$, ρ^{sc}, ρ^{sd}, $s^{\max}$, LE_h, χ_g and E^{co2} are grid price, storage operating cost, bid price, generation operating cost, market cleared supply, generator capacity factor, storage charging rate, discharging rate, maximal storage state, MGO residential electricity load, generator emission rate and carbon emission cap, respectively. $X_g^{\max}$ is generator capacity, and subject to investment decision. Variables eu_h, ec_h, ed_h, x_g^{uc}, $x_{h,g}$, $xu_{h,g}$ and s_h are electricity purchased from grid, storage charge, discharge, unsatisfied renewable supply, residential electricity supply, renewable electricity supply in energy market, and storage state. Equation (6) is MGO's profit optimization objective. Equation (7) is generation capacity constraint. Equation (8) is the storage state formulation. Equation (9) is storage discharging capacity. Equation (10) is maximal state constraint. Equation (11) is the supply and demand balance of residential electricity load. Equation (12) caps the total emissions of microgrids. Equation (13) is supply and demand balance of renewable electricity in energy market. Equation (14) is variables' non-negativities.

C. *Agent-based Simulation*

Microgrid operators are homogenous, and can be viewed as the same type of agents with different input parameters as differentiations. The utility company is modeled as a different agent.

The simulation framework is summarized in Fig. 2. The outer dash line frame is the planning layer, and the inner dash line frame is the operational layer implemented in the planning layer. Every microgrid operators would select an investment plans and goes to the operational layers. The operational layer returns the profits under this combination of investment plans of microgrid operators. At the beginning of every year, Microgrid agents start brand new learning procedure with learning parameters. Microgrid operator would reselect the investment plan based on the operational results until reach the terminal condition.

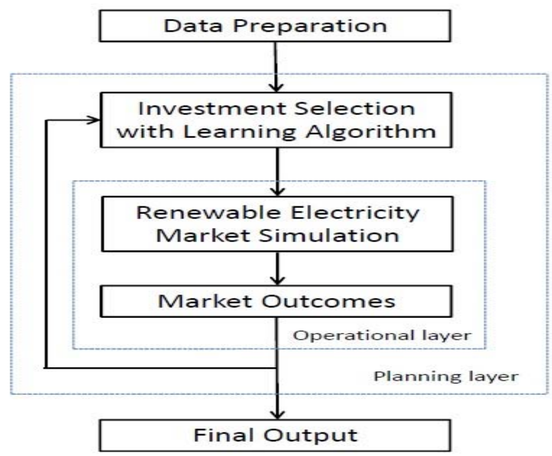

Fig. 2. Agent-based Simulation Framework

1) *Reinforcement Learning Algorithm*

We implement Roth-Erev reinforcement learning algorithm to model the agent's adaptive behavior [13,15]. The agents iteratively update their or choices based on (15)-(17).

$$O_{(t+1),a}^m = (1 - r^m) O_{t,a}^m + \mathrm{Response}_{t,a}^m \qquad (15)$$

$$\mathrm{Response}_{t,a}^m = \begin{cases} (1 - e^m)\mathrm{Profit}_{t,a}^m, \text{if a=a}' \\ e^m O_{t,a}^m / (\left|\mathrm{A}^m\right| - 1), \text{if a} \ne \text{a}' \end{cases} \qquad (16)$$

$$\mathrm{Prob}_{t,a}^m = \frac{\exp(O_{t,a}^m / C_t^m)}{\sum_a \exp(O_{t,a}^m / C_t^m)} \qquad (17)$$

where $O_{t,a}^m$ is propensity of agent m to choose action a in iteration t, and updated according to (15) and (16). Equation (17) is the choice probability of action a in iteration t. r^m is the damping parameter on the growth of propensities over time. e^m is the experimentation parameter [15]. C_t^m is the cooling parameters. $\text{Response}_{t,a}^m$ is reward function in the condition that agent m chooses action a in iteration t. $\text{Profit}_{t,a}^m$ is reward of agent m to choose action a in iteration t. $\left|\mathrm{A}^m\right|$ is cardinality of the action space A^m. For the utility company, Profit in (16) is replaced with utility $\text{Utility}_{t,a}^m$.

2) Action Spaces

In each year, the utility company has high, moderate, and low demand and price options, which is $3\times 3=9$ in total.

Action spaces of MGOs contain two parts, investment action space and operation action space. The latter one is subject to the former one. The baseline bidding price of MGO is defined as $\frac{IC_g}{\sum_{h,y}\eta_{h,g,y}}+OC_g^e$, where IC_g is per MW investment cost of generator g, $\eta_{h,g,y}$ is capacity factor of generator g at hour h in year y. The bidding price could range from 150% to 300% of the baseline price. We employed uniform distribution to randomly generate 9 bidding prices. The baseline bidding quantity of a given investment action is simply determined by the following equations:

$$\max \sum_{y,g\subset \text{clean}} q_{y,g}^b \tag{18}$$

$$\text{s.t.} \sum_g (\eta_{y,g} X_{y,g}^{\max} - q_{y,g}^b) = LE_y - eu_y \tag{19}$$

$$LE_y - eu_y \geq 0 \tag{20}$$

$$\eta_{y,g} X_{y,g}^{\max} - q_{y,g}^b \geq 0 \tag{21}$$

$$\sum_{g,y} \chi_g (\eta_{y,g} X_{y,g}^{\max} - q_{y,g}^b) \leq E^{\text{co2}} \tag{22}$$

$$q^b, eu \geq 0 \tag{23}$$

where $q_{y,g}^b$ is the baseline bidding quantity of generator g in year y. eu_y is daily total purchased electricity from grid in year y. LE_y is daily residential demand in year y. $\eta_{y,g}$ is daily accumulative capacity factor of generator g in year y, which is equal to summation of hourly capacity factor in one day. $X_{y,g}^{\max}$ is capacity of generator g in year y. E^{co2} is total emission cap of the whole planning horizon. Equation (18) tries to maximize total renewable energy supply. Equation (19) is supply and demand balance constraint. Equation (20) requires the purchased energy cannot exceed the load. Equation (21) says the baseline quantity is capped by generation availability. Equation (22) is carbon emission constraint. Equation (23) is variables' non-negativities.

The bidding quantity lies randomly between 50% to 120% of the baseline quantity, and less than the capacity. We employed uniform distribution to randomly generate 9 bidding quantities. Combining with 9 bidding prices, we determine 9 bidding actions in each year for MGOs.

Investment actions are designed by microgrid operator's preference and experience. We choose investment plans arbitrarily by considering economic scale and experience.

III. Numerical Example

In the numerical example, we consider ten microgrids and the utility company. The planning horizon is 20 years and each year has 365 days. The utility company is connected with microgrids via distributed lines.

Since in our problem, we focus on the planning rather than the operations, we assume within a year, systems are identical. In this way, it reduces uncertainties and the learning difficulties and complexities in the operational layer.

e^m and r^m of the utility company and MGOs in the investment layers are 0.85 and 0.14, respectively. e^m and r^m of MGOs in the operation layer are 0.8075 and 0.14, respectively. $C_t^m = 0.25\max_a\{O_{t,a}^m\}$ for all agents in each iteration. The load growth rates of MGOs are all 1.0% annually. Data of MGO investment and operation action space, UC action space, and investment costs are stored in file "DataIni.xls ." Carbon emission caps, emission rates of generators, operation costs, grid prices, electricity loads, total expansion capacities and capacity factors are stored in file "MGOdata.xls ." They are accessible via http://heyanyi.us/. Initial propensities of the utility company's actions are all 1.0. Initial propensities of microgrid operators are all 3.0E8 for investment actions, and 4.12E4 for operation actions. Lead times of all expanded generators are 2 years, and life times are all 20 years. Discount rate is 5%.

IV. Results

The problem is solved by using Java and executed on Linux operating system with 47G memory and 24 CPUs. It took about 12 to 15 minutes to complete one iteration. It takes 250 iterations to "converge". All the peaked probabilities are greater than 99%.

A. Investment Results

Table 1 lists the investment options with the peaked choice probability after simulation. MGO1 has rich wind and solar energy resources (high capacity factors), but small investment capacities. It is more profitable if MGO1 builds all new generations and earns renewable energy revenues as soon as possible, hence, MGO1 tends to choose Invest21. Similar reasons are applicable to explain MGO3, MGO5, MGO8 and MGO9. MGO2 has great supply ability of relatively cheaper wind power, thus, Invest2, which is to invest a lot of wind in the first year, is a better plan than others. MGO6 picks Invest16 due to its continuous investments from year 7 to 10, when systems' loads increase significantly and other MGOs don't have new investment around this time. Invest27 fits for MGO7 best in the study because small annual investment compensates increasing local load. MGO10 prefer Invest94 since Invest94 is to invest cheap biomass than digester.

Under modeled sophisticated behaviors, MGOs tend to have high expected returns on investment plans listed in the table. However, it is worth to note that there is no guarantee that they are the “optimal” decisions even under our framework, because there always exist probabilities that agents continue to perform the worst operations after investment. Nevertheless, if all the agents are rational and sophisticated, it is reliable and secure to choose the listed investment plans than others, because agents can perceive pitfall and adjust the actions to avoid getting stuck in the trough under predefined user learning behaviors.

TABLE I
INVESTMENT DECISIONS WITH PEAKED CHOICE PROBABILITIES OF MGOS

MGO1	MGO2	MGO3	MGO4	MGO5
Invest21	Invest2	Invest13	Invest54	Invest25
MGO6	MGO7	MGO8	MGO9	MGO10
Invest 16	Invest27	Invest81	Invest86	Invest94

B. Energy Market Results

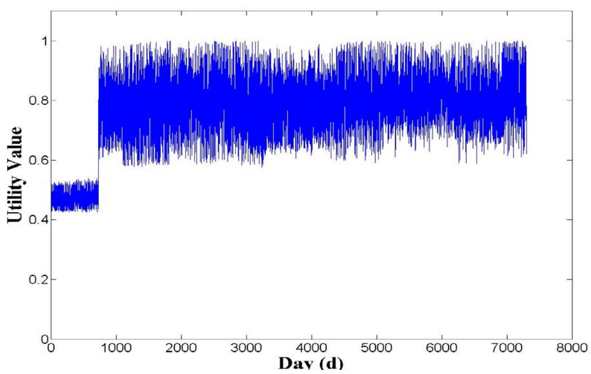

Fig. 3. Utility Values of UC

Fig. 3 -5 shows the bidding results (utility value, market cleared demand and market cleared payment , respectively) of the utility company under converged investment decisions of microgrid operators. They provide a general impression of operational simulation. Generally, the results of hourly market cleared payment and supply fluctuate rapidly, but overall trend of the payment and supply of the renewable energy are going up as time goes by. This result is consistent with the utility company's original intention that the renewable demand increases annually. The daily utility value has a jump at year 3. Because the utility company's high demand of renewable energy gets satisfied when the new generators complete the construction after two year lead time. After year 3, utility value fluctuates between 0.6 and 1.0.

The utility company only monitors daily utility value and adjusts it actions next day. It minimize its payment via (1)-(5) every day, and does not require a convergences in the investment layer. It begins a new learning process at the beginning of each year, it stops learning in the last day in a year, even if it does not converge. The environment is changing subject to investment decisions, and in real world, agents usually have not fully learned the changes when the systems evolve.

Without losing generality, MGO2 are selected to represent MGOs’ activities in the operational layer, when MGOs all select the listed investment plans in Table 1.

Generally, due to the random selection in the reinforcement learning algorithm, the profits fluctuate from day to day. However, the trend from year to year is apparent. For example, since we have two year lead time of the generator construction, both profits change significantly from year 3. The second year's profit is less than the first year, because increasing local demand and reduction in supply in the renewable market leads to drop in the second year profits. MGO2 have decreasing trend of renewable energy supply since year 3. Since the selected investment plan only built new generator in year 1and 2, the supply will be reduce due to the local demand growth. It also implies that the operational decision is consistent with the investment decisions.

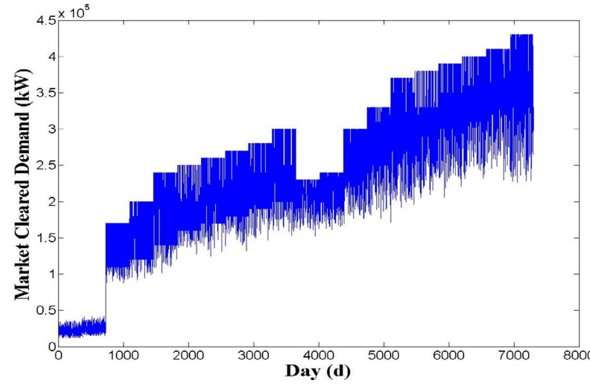

Fig. 4. Market Cleared Renewable Demand

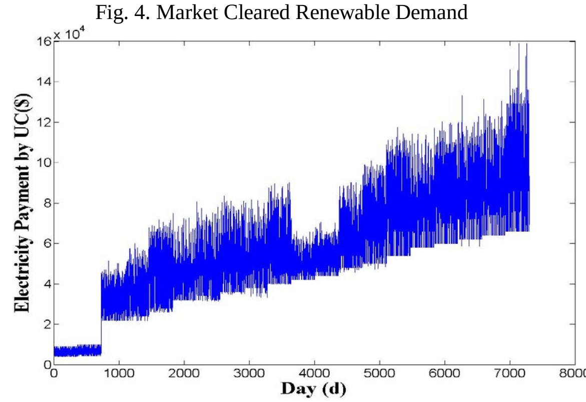

Fig. 5. Total Payment of Renewable Energy

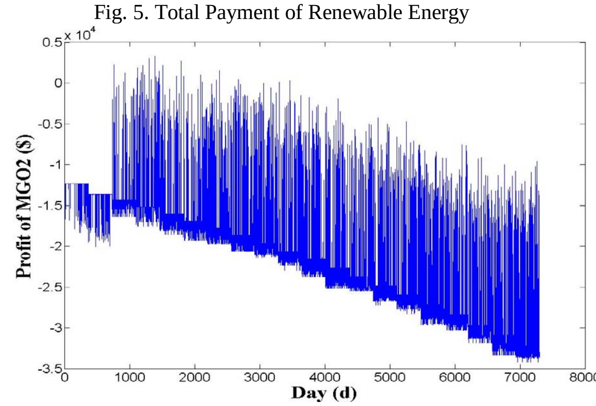

Fig. 6. Profit of MGO2

Fig. 7 can give more insights of the operation layer. It is the histogram of MGO2’s profit in year 3 (random selected year) in the last 165 days. It is obvious that most of profits lie in one block. It could imply that MGO2 agent gets familiar with market quickly in this year to come up with a frequent profit. Another observation is profit ranges broadly. It reflects market complexities. Even MGO2 agent takes the same action, market results may change significantly due to other agents' actions. Negative profit is because residential electricity generation cost is much higher than revenue in the renewable market. Other profits can be analyzed in the similar way. Generally, the renewable supply in the market depends both on the investment decisions and local electricity demand.

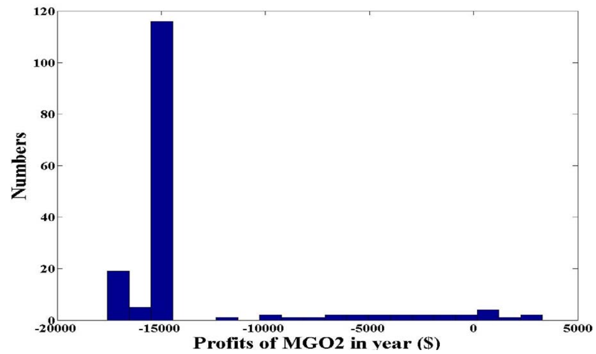

Fig. 7. Histogram of MGO2 Profit in Year 3

V. DISCUSSION

In general, we believe higher propensity means higher probability to be a better investment plan under the learning behavior. The "best" investment plans of each microgrid operators stand out as simulation goes on. It is interesting to observe that the operational layer's results fluctuate rapidly, while the investment layer's probability results come to a peak within 250 iterations. It is because investment layer's propensity is the accumulative result of the operational layer. If one investment plan is better than another one, in the operational layer, it tends to accumulate more profits in the simulation. The accumulated profits of 7300 days could be significant to differentiate the investments.

The dynamic cooling parameters make agents experimenting across their action domains, slow down the convergence speed and avoid premature convergence of using constant cooling parameters. Since the investment profits are large and place a large impact on the propensity and easily induce peaked choice probabilities with constant cooling parameters after a few propensity updates.

VI. CONCLUSION

We implement agent-based simulation on a distributed energy market to study the complex long-term investment competition behaviors among microgrid operators. Fluctuating results in the operational layer have minor effect on the convergence of the investment layer. This simulation framework can be implemented to put emphasis on real time pricing in the energy market, centralized planning of aggregated MGOs or single MGO planning in competitive market with large-scaled real case study.

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VIII. BIOGRAPHIES

Yanyi He Y. He is currently a Ph.D candidate in Department of Industrial and Manufacturing System Engineering at Iowa State University. She received her B.S. degree in Physics from University of Science and Technology of China in 2007, followed by a M.S degree in Physics from Iowa State University in 2009. She also worked as an intern in NEC labs America from May to August, 2011. Her current research interests include environmental policies, power system planning, power market optimization and microgrids modeling.

Ratnesh Sharma Ratnesh leads the Energy Management Department at NEC Laboratories America. He has a PhD degree from University of Colorado at Boulder and BTech. (Hons.) degree from Indian Institute of Technology, Kharagpur. His research interests span sustainable energy management in electricity, buildings and transportation sectors including energy conversion, power systems, communications and analytics. He has authored more than 135 papers/technical reports and holds 50 US patents.