Comparison of Theoretical and Simulation Analysis of Electricity Market for Integrative Evaluation of Renewable Energy Policy

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Abstract: Governments have introduced various policies for promoting renewable energy technologies. In particular, feed-in tariff (FIT) and renewable portfolio standard (RPS) have been introduced in various countries. In this work, multi-agent simulations of electricity markets with FIT/RPS have been conducted for integrative analysis and rational design of renewable energy policies. We analyze the effects of the FIT price and RPS level on social welfare. By comparing the results obtained from the simulation and the equilibrium analysis, we have examined the policies from both bottom-up and top-down viewpoints comprehensively.

1 INTRODUCTION

In recent years, emissions of greenhouse gases such as carbon dioxide and methane have been implicated in the worldwide problem of global warming. One of the solutions being implemented to solve the problem is to increase the adoption of renewable energy (RE) to in turn reduce emissions of greenhouse gases. However, the cost of RE production is high. Governments have introduced various policies for promoting RE technologies. In particular, feed-in tariff (FIT) and renewable portfolio standard (RPS) have been introduced in various countries. FIT is a scheme that requires non-renewable energy (NRE) producers to purchase RE at fixed FIT prices. RPS requires that a certain percentage of NRE producers' electric generation capacity come from RE. RE producers issue and sell renewable energy certificates (REC) to NRE producers in REC markets to comply with the RPS requirement percentage.

There have been few studies discussing whether FIT or RPS is preferable from the aspect of social welfare. (Hibiki and Kurakawa, 2013) explored how FIT and RPS affect social welfare in the case of only one NRE producer and one RE producer in an electricity market by theoretical analysis. Their findings indicated that governments should introduce RPS when marginal damage cost is relatively high. They did not evaluate the effect of the number of NRE and RE producers or market structure. (Siddiqui et al., 2016) studied how RPS requirement percentage and market structure affect social welfare under RPS. They determined the optimal RPS requirement percentage and suggested the importance of considering market structure for setting the optimal RPS requirement percentage to maximize social welfare. (Nishino and Kikkawa, 2013) studied the interdependent effects of multiple energy policies by theoretical analysis and multi-agent simulation. However, they did not discuss the results from the aspect of social welfare.

Our purpose is to clarify how the relationships among policy, market power, and number of producers impact social welfare. In this work, multi-agent simulations of FIT and RPS are conducted for integrative analysis and rational design of renewable energy policies. Multi-agent simulations enable us to evaluate more realistic market and to observe emergent processes of equilibrium states. By comparing the results obtained from the simulation and the equilibrium analysis, we comprehensively examine the policies from both bottom-up and top-down viewpoints.

2 METHODS

For simplicity, in this manuscript, we show the case of only one NRE producer and one RE producer in an electricity market.

2.1 Equilibrium Analysis

The single-level model for determining maximum social welfare is called Central planning (CP). In CP, a

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central planner decides all power plants' capacity so as to maximize social welfare. Markets with FIT or RPS are analyzed within the bi-level model. At the lower level, NRE and RE producers decide generation capacity to maximize their own profits. At the upper level, policymaker decides the optimal FIT price or RPS requirement percentage to maximize social welfare.

2.1.1 Central Planning

Social welfare *SW* is defined and maximized as follows:

$$\begin{aligned} SW \equiv\ & A(q_n+q_r)-\frac{1}{2}Z(q_n+q_r)^2 \\ & -C_n(q_n)-C_r(q_r)-D_n(q_n), \end{aligned} \tag{1}$$

$$\begin{aligned} \max_{q_n\geq 0, q_r\geq 0}\ & A(q_n+q_r)-\frac{1}{2}Z(q_n+q_r)^2 \\ & -C_n(q_n)-C_r(q_r)-D_n(q_n) \end{aligned} \tag{2}$$

where electricity price p shows linear inverse demand function (i.e., $p = A - Z(q_n+q_r)$) (in US dollars (USD)), A is the intercept of linear inverse demand function, Z is the slope of linear inverse demand function, q_n is NRE production (in MWh), and q_r is RE production (in MWh). The third, fourth and fifth terms in Eq.(1) are cost functions. Here, $C_n(q_n) = \frac{1}{2}c_n q_n^2$ is the cost function for NRE production, $C_r(q_r) = \frac{1}{2}c_r q_r^2$ is the cost function for RE production, $D_n(q_n) = \frac{1}{2}k q_n^2$ is the damage cost function for NRE production, and $c_n, c_r, k > 0$ are constants (in USD/MWh^2). The optimal solution of CP is obtained by solving Eq.(2) and is as follows:

$$\bar{q}_n = \frac{Ac_r}{c_r(Z+c_n+k)+Z(c_n+k)} \tag{3}$$

$$\bar{q}_r = \frac{A(c_n+k)}{c_r(Z+c_n+k)+Z(c_n+k)} \tag{4}$$

$$\bar{p} = \frac{A\{c_r(Z+c_n+k)+Z(c_n+k)\}-ZA\{(c_n+k)+c_r\}}{c_r(Z+c_n+k)+Z(c_n+k)} \tag{5}$$

$$\bar{\alpha} = \frac{c_n+k}{c_n+k+c_r} \tag{6}$$

where $\bar{q}_n$ and $\bar{q}_r$ are optimal NRE and RE production, respectively, $\bar{p}$ is optimal electricity price, and $\bar{\alpha}$ is optimal proportion of RE.

2.1.2 FIT

At the lower level, we now consider payoff functions for the NRE producer and RE producer:

$$\pi_n = p(q_n+q_r)-C_n(q_n)-p^{FIT}q_r \tag{7}$$

$$\pi_r = p^{FIT}q_r - C_r(q_r) \tag{8}$$

where p^{FIT} is FIT price. When the NRE producer is dominant and behaves *à la* Cournot, optimal solution is as follows:

$$\tilde{q}_n = \frac{Ac_r-2Zp^{FIT}}{c_r(2Z+c_n)} \tag{9}$$

$$\tilde{q}_r = \frac{p^{FIT}}{c_r} \tag{10}$$

$$\tilde{p} = \frac{Ac_r(Z+c_n)-Zc_np^{FIT}}{c_r(2Z+c_n)} \tag{11}$$

$$\tilde{\alpha} = \frac{(2Z+c_n)p^{FIT}}{Ac_r+c_np^{FIT}} \tag{12}$$

At the upper level, we maximize social welfare about p^{FIT}:

$$\begin{aligned} \max_{p^{FIT}}\ & A(\tilde{q}_n+\tilde{q}_r)-\frac{1}{2}Z(\tilde{q}_n+\tilde{q}_r)^2 \\ & -C_n(\tilde{q}_n)-C_r(\tilde{q}_r)-D_n(\tilde{q}_n) \end{aligned} \tag{13}$$

As a result, we obtain the following optimal FIT price $\tilde{p}^{FIT}$:

$$\tilde{p}^{FIT} = \frac{Ac_r(3c_nZ+2Zk+c_n^2)}{4Z^2(k+c_n)+c_n^2Z+c_r(2Z+c_n)^2} \tag{14}$$

2.1.3 RPS

At the lower level, we now consider payoff functions for the NRE producer and RE producer:

$$\pi_n = pq_n - C_n(q_n) - \alpha p^{REC}q_n \tag{15}$$

$$\pi_r = pq_r - C_r(q_r) + (1-\alpha)p^{REC}q_r \tag{16}$$

where p^{REC} is REC price, α is RPS requirement percentage. When the NRE producer is dominant and behaves *à la* Cournot, optimal solution is as follows:

$$q_n^* = \frac{A(1-\alpha)}{(2Z+c_n+c_r)\alpha^2-2(Z+c_n)\alpha+(2Z+c_n)} \tag{17}$$

$$q_r^* = \frac{A\alpha}{(2Z+c_n+c_r)\alpha^2-2(Z+c_n)\alpha+(2Z+c_n)} \tag{18}$$

$$p^* = \frac{A\{(2Z+c_n+c_r)\alpha^2-2(Z+c_n)\alpha+(Z+c_n)\}}{(2Z+c_n+c_r)\alpha^2-2(Z+c_n)\alpha+(2Z+c_n)} \tag{19}$$

$$p^{*\ REC} = \frac{A\{(2Z+c_n+c_r)\alpha-(Z+c_n)\}}{(2Z+c_n+c_r)\alpha^2-2(Z+c_n)\alpha+(2Z+c_n)} \tag{20}$$

At the upper level, we maximize social welfare about α:

$$\begin{aligned} \max_{\alpha}\ & A(q_n^*+q_r^*)-\frac{1}{2}Z(q_n^*+q_r^*)^2 \\ & -C_n(q_n^*)-C_r(q_r^*)-D_n(q_n^*) \end{aligned} \tag{21}$$

We solve the above equation numerically to find the optimal RPS requirement percentage α^*.

2.2 Multi-agent Simulation Analysis

In this work, the deregulated electricity market consists of NRE producer agents, RE producer agents and consumers expressed as the linear inverse demand function, and is modeled as the blind and single-price call auction with reference to (Nishino and Kikkawa, 2013). In this auction, each energy producer agent offers its asking price and production. All orders are aggregated into the market schedules of supply and demand, and their intersection determines a single, market-clearing price for all feasible quantities (Figure 1).

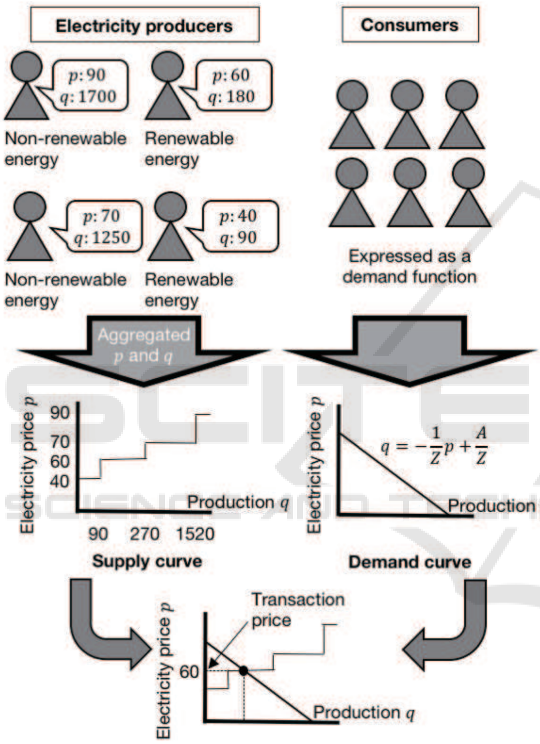

Figure 1: Trading mechanism of multi-agent simulation.

Each agent learns the optimal pricing strategies based on the Q-learning method (Watkins and Dayan, 1992) in order to maximize its profit. The Q-learning procedure used in this work is described below:

1. Decide action based on Q-value by softmax selection with Boltzmann distribution:
$$Prob(a|s) = \frac{\exp\{Q(s,a)/T\}}{\Sigma_{a'}\exp\{Q(s,a')/T\}} \tag{22}$$
where $s = s(p_n^{ask}, p_r^{ask})$ is the state of the market, p_n^{ask} and p_r^{ask} are the asking-price of NRE and RE producer agents respectively, $a \in \{p^{ask}+1, p^{ask}\pm 0, p^{ask}-1\}$ is the action of each producer agent, $Q(s,a)$ is Q-value, $T > 0$ is the "temperature".
2. Calculate the asking-quantity of production of each producer agent as the optimal response for each updated p^{ask}.
3. Decide transaction price and actual quantity of production of each producer agent.
4. Calculate profit of each producer agent and social welfare.
5. Update Q-value of each producer agent using the following equation:
$$\begin{aligned} Q(s_t,a) \leftarrow\ & (1-\beta)Q(s_t,a) \\ & + \beta\{r_t/100 + \gamma \max_a Q(s_{t+1},a)\} \end{aligned} \tag{23}$$
where s_t is the state at the t learning step, β is learning rate, $r_t \equiv (\pi_t - \pi_{t-1})$ is the reward of each producer agent at the t learning step, π_t is the profit of each producer agent at the t learning step, and γ is the discount rate.
6. End search if the maximum number of learning steps is reached.

We now consider a electricity market with no renewable energy policy and then obtain the following payoff functions:

$$\pi_n = pq_n - C_n(q_n) \tag{24}$$

$$\pi_r = pq_r - C_r(q_r) \tag{25}$$

Optimal asking-quantity of production q^{ask} for an asking-price p^{ask} is:

$$q_n^{ask} = \frac{p_n^{ask}}{c_n} \tag{26}$$

$$q_r^{ask} = \frac{p_r^{ask}}{c_r} \tag{27}$$

3 RESULTS AND DISCUSSION

We evaluate the effect of the renewable energy policy from the aspect of social welfare. Table 1 shows the evaluation conditions. The parameter values were set by reference to (Hibiki and Kurakawa, 2013) and (Nishino and Kikkawa, 2013).

Figure 2 shows learning history about pricing of each producer agent. Asking-prices of both producer agents converge to specific values. Consequently, transaction price, actual supply quantity of each producer agent and social welfare also converge to specific values (Figure 3 and Figure 4 (top)). Figure 4 (bottom) and Table 2 show comparison of social welfare, energy production, proportion of RE and electricity price between equilibrium analysis and multi-agent simulation. Compared with CP, FIT leads to

Table 1: Evaluation conditions.

	Parameter		Value	Unit
Demand	Intercept of inverse demand function	A	100	USD
	Slope of inverse demand function	Z	0.01	USD/MWh
Cost	Coefficient of NRE production cost	c_n	0.025	USD/MWh^2
	Coefficient of RE production cost	c_r	0.25	USD/MWh^2
	Coefficient of damage cost	k	0.025	USD/MWh^2
Q-learning	Maximum number of learning step	t_{max}	200,000	-
	Temperature	T_t	$50 \times (0.99995)^t$	-
	Learning rate	β	0.5	-
	Discount rate	γ	0.5	-

higher NRE production cost and damage cost while RPS leads to higher RE production cost. We can see that multi-agent simulation (MAS) with no renewable energy policy yields higher producer surplus, lower proportion of RE, higher damage cost, and as a result, social welfare indicates the smallest value.

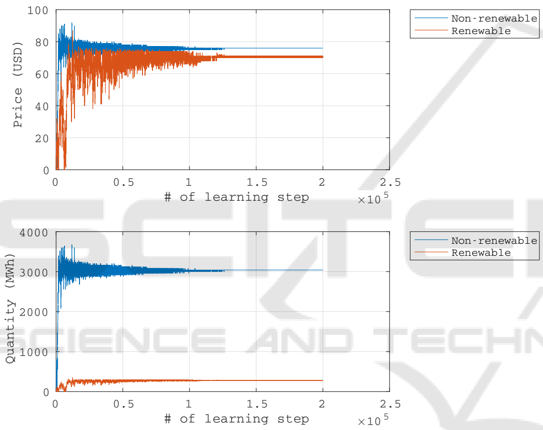

Figure 2: Asking electricity price (top) and quantity (bottom) of each producer agent.

4 CONCLUSIONS

We modeled the deregulated electricity market as the blind and single-price call auction, and constructed multi-agent system in order to clarify how the relationships among renewable energy policy, market power, and number of producers impact social welfare. Under the conditions of this evaluation, RPS achieved superior social welfare value to FIT and MAS (with no renewable energy policy). Additional numerical experiments and assessments of the market dynamics that specifically take into account realistic diversity of agents' characteristics and various uncertainties are important topics for future research.

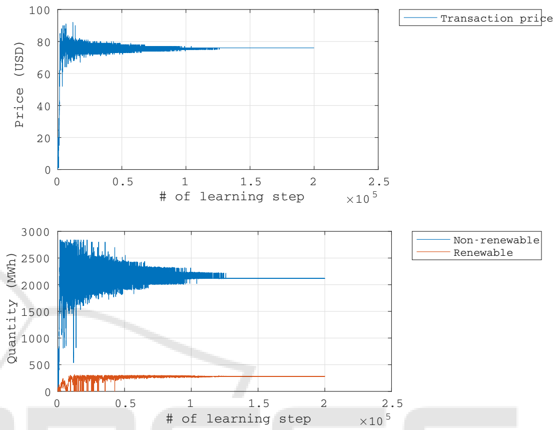

Figure 3: Transaction price (top) and actual supply quantity of each producer agent (bottom).

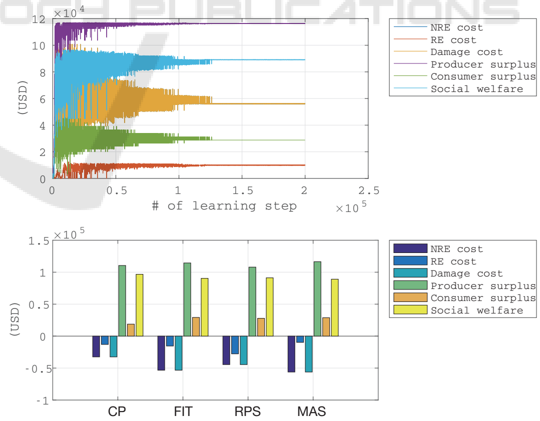

Figure 4: Breakdown of social welfare: (top) Convergence history of multi-agent simulation, (bottom) Comparison between equilibrium analysis and multi-agent simulation.

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Table 2: Comparison between equilibrium analysis and multi-agent simulation.

	CP	FIT	RPS	MAS
NRE production cost (USD)	-32,522	-53,354	-44,557	-56,180
RE production cost (USD)	-13,041	-15,488	-27,730	-9,800
Damage cost (USD)	-32,522	-53,354	-44,557	-56,180
Producer surplus (USD)	110,478	114,442	107,941	116,420
Consumer surplus (USD)	18,740	29,234	27,824	28,800
Social welfare (USD)	96,697	90,321	91,208	89,040
NRE production (MWh)	1,613	2,066	1,888	2,120
RE production (MWh)	323	352	471	280
Total production (MWh)	1,936	2,418	2,359	2,400
Proportion of RE (-)	0.17	0.15	0.20	0.12
Electricity price (USD/MWh)	80.6	75.8	76.4	76

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