Decentralized Trading and Demand Side Response in Inter-Intelligent Renewable Energy Network

Tadahiro Taniguchi
Department of Information Science & Engineering
Ritsumeikan University
Shiga, Japan
Email: taniguchi@ritsumei.ac.jp

Shiro Yano
Research Organization of Science and Technology
Ritsumeikan University
Shiga, Japan
Email: s_yano@em.ci.ritsumei.ac.jp

Abstract—We propose the use of a new decentralized autonomous smart grid model involving adaptive trading agents which can sell and buy electric power in a local electric power network. We name the electric power network inter-intelligent renewable energy network, i-Rene. Trading agents in the local grid manage the amount of electric power generated by PV or other renewable energies stored in batteries in residences. The agents learn trading policies by maximizing their profits. Based on the proposed system, we evaluated its price formation and effectiveness of the adaptive trading method analytically. To model demand side management which can control the amount of electric power consumption, developing an elastic additional consumption model is essential. We added an elastic additional consumption model to the model. We also performed a simulation experiment with a hundred agents and additional noise term for load profiles.

I. INTRODUCTION

Recently, PVs and other renewable energies including wind power and bioethanol are attracting a great deal of attention because fossil fuel will become difficult to mine in the near future. Fossil fuel is an exhaustible resource in contrast with solar energy and wind power which are renewable resources. However, electric power generated by PV and wind power is unpredictable because it depends on weather and climate. Therefore, finding how to adapt consumers’ demand to the unpredictable and fluctuating supply is key issue when we develop our future electric power network system. Recently, a decentralized autonomous electric power network has been studied as a way to overcome this problem [1].

A decentralized autonomous electric power network has two properties. The first one is that the network has energy resources including PV panels, wind power generators, and batteries in a distributed way. Such resources are called distributed energy resources (DER). The virtual power plant (VPP) is a series of researches about managing DER in a micro grid [2], [3], [4]. Pudjianto et al. studied the concept and system architecture of VPP [2]. Kok et al. studied bidding behaviors in VPP from the viewpoint of economics [3]. Chalkidils et al. proposed a pricing mechanism in the Cooperative VPP (Cooperative VPP). The VPP is a broad concept.

The second one is planning and controlling DER in a distributed way. Many generators, batteries and loads are considered as a kind of multi-agent system. Every agent independently makes decisions and buys or sells its electric power [1], [5]. They have also been studied from the viewpoint of game theory [6], [7]. We discuss the decentralized autonomous electric power network having both of the above properties.

On the basis of this background, we proposed an inter-intelligent renewable energy network (i-Rene). A schematic of i-Rene is shown in Fig. 1. In i-Rene, a locally generated electric power is basically consumed in the local grid. In the current electric power network in Japan, the surplus energy produced by PV is sold and flown to a grid managed by a regionally monopolizing electric power company. This causes reverse power flow. There is concern that a high level of reverse power flow will make the global electric power network unstable.

Therefore, surplus energy in i-Rene is designed not to be flown out to its outside grid. A gateway connects i-Rene and its outside grid transmits electric power in a single direction. A power router, or a smart meter, equipped in each house in i-Rene has an intelligent computer agent. The agent automatically trades electricity in the local electricity market and allocates generated electricity appropriately by referring to the load profile of each house. We assume that the electric power network covers a town. The number of houses in a town is assumed to be approximately between ten to several thousands. Because of the assumption, we assume that the loss of electric power transmission is really small and can be ignored in the i-Rene model described here.

In i-Rene, we assume that each house has a generator using renewable energy and a battery. An agent in a house automatically trades electricity on behalf of the dweller because a person living in the house cannot always trade electricity because of the time constraints of daily life. The agent learns its trading policy so as to maximize the dweller’s profit. However, local power generation and trading cannot satisfy all of the loads in the local grid when the sum of the amount of generation and SOC of the batteries is smaller than the total consumption in the local grid. In such a case, the agents in i-Rene have to buy electricity from an outside power grid through its gateway. They can buy electricity from the outside grid at the price of grid price $p_c^G$ in any time.

Recently, automatic trading of electric power has been
A. Basic assumptions

As shown in Fig. 2, each house has a power router which is a type of a smart meter controlling the residence’s battery and communicating with electricity market. The power router receives a load profile $l_i^t$, a battery profile $b_i^t$, and a market shipping profile $m_i^t$ as follows.

\[
l_i^t = e_i^{\text{consumption},i} - e_i^{\text{generation},i}
\]
\[
b_i^t = e_i^{\text{charge},i} - e_i^{\text{discharge},i}
\]
\[
m_i^t = e_i^{\text{sell},i} - e_i^{\text{buy},i}
\]

The load profile $l_i^t$ is a difference between electricity consumption $e_i^{\text{consumption},i}$ and electricity generation $e_i^{\text{generation},i}$. The battery profile $b_i^t$ is a difference between charging $e_i^{\text{charge},i}$ and discharging $e_i^{\text{discharge},i}$. The market shipping profile $m_i^t$ is a difference between the amount of electricity the house sells $e_i^{\text{sell},i}$ and it buys $e_i^{\text{buy},i}$. $i$ is an index of a house and $t$ is an index of time. $e_i^{+,i}$ is a non-negative value. In this model, we ignore transmission loss and energy loss for charging. We consider i-Rene as a local network. Therefore, the distance between two houses is not so far. This means that transmission loss is vanishingly small. Energy loss involved in charging batteries is significant. However, electric double-layer capacitor (EDLC) and other innovative device will reduce this loss in the near future. In this context, we make the above assumptions.

In this case, following Kirchhoff’s law is satisfied.

\[
l_i^t + b_i^t + m_i^t = 0
\]

As far as $s_i^t$ does not reach its boundaries, $s_i^t$ satisfies following equation.

\[
s_{i+1}^t = s_i^t - l_i^t - m_i^t = s_i^t + b_i^t
\]

where $s_i^t$ represents state of charge (SOC) of the $i$-th home’s battery. The maximal value of $s_i^t$ is defined to be $S_{\text{max}}$. We take a notation that the symbols which have been eliminated index $i$ means a value calculated by summing up the value over $i$.

B. Autonomous Trading Agent

Each agent learns each trading policy on the basis of its utility. We assume that each individual demand curve and supply curve which are the main components of a trading policy are linear functions. Under this assumption, we derive an agent learning algorithm and analyze system dynamics of the economical electric power network.

First, we assume that a price on a demand supply curve is 0 when a battery’s state of charge (SOC) is full. Its marginal value of SOC should be 0 because additional charging will not give any additional benefit to the individual home. This enable us to define a function $f_i^t$ which maps a price $p$ to SOC $s_i^t$ as follows.

\[
f_i^t(p) = -\frac{S_i^t}{p_i^t} p + S_{\text{max}}^t
\]

This does not mean that we each demand supply curve of each person living in this system is approximated by linear function. This is about machine agents. This is an engineering issue.
C. Learning algorithm

We derive the market shipping profile \( m_t^i \) on the basis of this assumption. If we assume that all of the battery is not either full or empty, and if transmission loss and energy loss for charging is 0, the sum of market shipping profiles become 0.

\[
0 = \sum_i -m_t^i = \sum_i (b_t^i + l_t^i) = \sum_i (s_{t+1}^i - s_t^i + l_t^i) = \sum_i (f_t^i(p_t^i) - (s_t^i - I_t^i))
\]

where \( p_t^i \) is a market price of the system. In this case, the best policy for a trading agent is to sell or buy electric power until its SOC reaches \( f_t^i(p_t^i) \). This enables us to determine market price uniquely to be

\[
p_t^i = \gamma H(p_t^i; \omega)
\]

where

1. \( \gamma = \frac{S_{\text{max}}}{S_{\text{max}} - s_t^i + l_t^i} \) is an additional charging capability of the local grid.

\( H(p_t^i; \omega) \) is a weighted harmonic average of \( n \) variables \( x \) with a weight vector \( \omega \) as follows.

\[
H(x; \omega) = \left( \sum_i \omega_i \frac{1}{x_i} \right)^{-1}
\]

This equation means that

1) The price become higher when the electricity gets lower,
2) The agent with a larger battery affects the market price more.

These results look natural and easy to understand. In this case, a market shipping \( m_t^i \) by the \( i \)-th agent at time \( t \) becomes

\[
m_t^i = S_{\text{max}} \left( \frac{p_t^i}{p_t^i} - \frac{S_{\text{max}} - s_t^i + l_t^i}{S_{\text{max}}} \right).
\]

C. Learning algorithm

An agent changes its trading policy to maximize its profit. The profit \( \phi_t^i \) of the \( i \)-th agent at time \( t \) becomes

\[
\phi_t^i = p_t^i m_t^i = p_t^i S_{\text{max}} \left( \frac{p_t^i}{p_t^i} - \frac{S_{\text{max}} - s_t^i + l_t^i}{S_{\text{max}}} \right).
\]

An agent’s trading policy depends only on individual maximal price \( p_t^i \). An agent changes \( p_t^i \) so as to maximize its total profit. For simplicity, we introduce a proxy variable \( y_t^i \) used on behalf of \( p_t^i \) as follows.

\[
p_t^i = \exp(y_t^i)
\]

\( y_t^i \) is a logarithm of \( p_t^i \). We call \( y_t^i \) log-individual maximal price.

All of the agents try to maximize their profits by changing \( y_t^i \). In addition, we assume the number of agents in a local network is big enough. Therefore, small changes in \( y_t^i \) hardly affect market price \( p_t^i \). Changes in \( y_t^i \) only affect \( \phi_t^i, \phi_{t+1}^i \) directly. They affect \( p_{t+1}^i \) indirectly via changes in \( s_{t+1}^i \). Gradients of \( \phi_t^i \) and its update formula are derived as follows.

\[
\frac{\partial \phi_t^i}{\partial y_t^i} = S_{\text{max}}(p_t^i - p_t^i)p_t^i
\]

\[
y_t^i \leftarrow y_t^i + \eta \frac{\partial \phi_t^i}{\partial y_t^i}
\]

where \( \eta \) is a learning coefficient and determines the speed of learning.

D. Exception handling

We described the learning algorithm when SOC does not reach either full or empty. When SOC goes under the battery’s minimal value, the agent fills in the gap by buying electricity from an outside grid or generates electricity by paying an additional cost at a price of the grid price \( p_t^G \). Exception handling for an empty situation is described as

\[
s_{t+1}^i = \max(0, f_t^i(p_t^i)).
\]

When \( f_t^i < 0 \), the local agent has to pay a certain amount of money to the outside grid. The agent’s profit becomes

\[
\phi_t^i = p_t^i f_t^i(p_t^i) = p_t^i S_{\text{max}} \left( 1 - \frac{p_t^i}{p_t^G} \right).
\]

The update formula becomes

\[
\frac{\partial \phi_t^i}{\partial y_t^i} = S_{\text{max}}(p_t^{i+1} - p_t^G)p_t^i \exp(-y_t^i).
\]

E. Analysis of price fluctuation

If all the agents learn and change their policies, the market price gradually changes. The effects of changes in \( y_t^i \) can be analytically evaluated as follows.

\[
\frac{\partial p_t^i}{\partial y_t^i} = \gamma \sum w_t \exp(-y_t^i)^2
\]

\[
\frac{\partial p_{t+1}^i}{\partial y_t^i} = -S_{\text{max}} p_t^i \exp(-y_t^i)H(p_t^i, w)
\]

Based on this result, we obtain

\[
p_t^i < p_t^{i+1} \rightarrow y_t^i \uparrow \rightarrow p_t^i \uparrow p_t^{i+1} \downarrow \quad \text{(23)}
\]

\[
p_t^i > p_t^{i+1} \rightarrow y_t^i \downarrow \rightarrow p_t^i \downarrow p_t^{i+1} \uparrow \quad \text{(24)}
\]

These equations mean that the market price becomes smooth by reducing gaps between \( p_t^i \) and \( p_t^{i+1} \). \( \uparrow, \downarrow \) mean that the value increases or decreases on the basis of left-side event of \( \rightarrow \), respectively. As a result, it is expected that optimization of circulating electricity within the local network and price equalization is achieved simultaneously.
F. Modeling demand response with utility function of electricity consumption

1) Elastic additional consumption: In the above assumptions, \( l_i^t \) is fixed and does not change with the fluctuated price \( p_i^t \). This model cannot be used for modeling demand response behavior. We add an additional term \( d_i^t \) representing elastic additional consumption fluctuated referring to the market price \( p_i^t \). We call the model including such elastic additional consumption elastic additional consumption model. A load profile including additional consumption \( d_i^t \) is now defined to be \( L_i^t \) as follows.

\[
L_i^t = l_i^t + d_i^t \tag{25}
\]

If an additional consumption \( d_i^t \) is positive, the \( i \)-th home consumes more electricity than \( l_i^t \) at time \( t \). If \( d_i^t \) is negative, the home consumes less electricity than \( l_i^t \). In this case, Eq.(26) is satisfied under the same conditions as before.

\[
L_i^t + b_i^t + m_i^t = 0 \tag{26}
\]

An utility \( \phi_i^t \) of \( i \)-th home at time \( t \) is defined to be

\[
\phi_i^t = p_i^* m_i^t + D_i^t \tag{27}
\]

where utility of additional consumption \( D_i^t \) represents utility about additional consumption of people living in the \( i \)-th home. \( D_i^t \) can take a variety of functions. We take

\[
D_i^t = \alpha_i^t (1 - \exp(-\beta_i^t d_i^t)) \tag{28}
\]

as an example of utility function for additional consumption. This is a monotonously increasing convex function. \( \alpha_i^t \) and \( \beta_i^t \) are shape parameters for the utility function. The shape of the utility function determines the consumer’s elasticity of demand to price.

2) Demand side adaptation: Each agent can increase its profit \( \phi_i^t \) by changing \( d_i^t \). By differentiating the profit \( \phi_i^t \) partially by \( d_i^t \), we obtain

\[
\frac{\partial \phi_i^t}{\partial d_i^t} = -p_i^* + \alpha_i^t \beta_i^t \exp(-\beta_i^t d_i^t). \tag{29}
\]

The equilibrium condition of above equation can be found at

\[
d_i^t = -\frac{1}{\beta_i^t} \log \left( \frac{p_i^*}{\alpha_i^t \beta_i^t} \right). \tag{30}
\]

By using this information, we can update \( d_i^t \) for each step. This equation means that \( d_i^t \) is solely affected by \( p_i^t \).

III. EXPERIMENT

A. Conditions

In this section, we evaluate our analytical result for price formation proved in the previous section through numerical simulation. An experiment in this section used virtual data drawn from some probability distributions because we do not have a sufficient number of accurate real data sets that include elasticity of demand, load profiles of all houses in a town, and PV generation. We define a base load profile \( l_i^t \) of each agent as

\[
l_i^t = -A^t \cos \left( 2\pi t + t_i^0 \right) \times (1 + \epsilon_i^t). \tag{31}
\]

where \( A \) is a gain constant, \( t_0 \) is an offset of time axis , and \( T \) is the number of time slots for trading. In the above equation, \( \epsilon_i^t \) is a noise term which is not considered in section 2. However, the both of consumption data and power generation data are not deterministic in a real environment. Therefore, we introduce a multiplicative noise term \( \epsilon_i^t \) which probabilistically change over time.

In this experiment, we set the number of agents \( N = 100 \), grid price \( p_G = 20 \), an initial SOC \( s_0 = 5 \), the number of time slots for trading \( T = 24 \), the learning coefficient \( \alpha = 0.01 \) and the battery size \( S_{\text{max}} = 10 \). The gain of the base load profile was \( A = 2 \). Other variables representing the characteristics of each home was drawn from corresponding distributions as follows.

\[
t_i^0 \sim \text{N}(0,4)
\]

\[
\bar{\beta}^i \sim \text{Gam}(2,1)
\]

\[
\beta^i = \bar{\beta}^i + 1
\]

The multiplicative noise term \( \epsilon_i^t \) was drawn from a normal distribution.

\[
\epsilon \sim \text{N}(0,0.2) \tag{32}
\]

Sampled base load profiles are shown in Fig. 3(top).

B. Result

First, Fig. 3 shows the load profiles \( l_i^t \) of seven houses before and after learning. The additional consumption \( d_i^t \) profiles are shown in Fig. 5 in a similar way. The load profiles aggregated over the hundred houses are shown in Fig. 4. These show that the mechanism adaptively equalizes load profiles and cuts peak loads. The effect of the equalization did not occur uniformly at each load profile, but it equalized the aggregated load profile as a whole.

Price fluctuations for four days with the same initial SOC before and after learning are shown in Fig. 6, and Fig. 8 shows electricity inflow from the outside grid. The positive value represents electricity inflow from the outside grid and the negative value represents energy losses in the local grid. Fig. 7 shows SOC profiles of batteries in seven residences. First, the agent could not trade electricity efficiently and caused energy losses and additional electricity inflow from an outside grid (Fig. 8). When all the SOC’s of all the batteries reached full, the market price naturally went down to 0. However, when the SOC of all batteries reached empty, the market price went up to the grid price \( p_G = 20 \). For this reason, the price fluctuated dynamically before the learning period. However, the price fluctuation flattened after learning the trading policy and updating additional consumption adaptively.

\( ^2 \)As we described, i-Rene does not permit reverse power flow like Feed-in Tariff
because of the noise terms and the exception handlings. These show that the i-Rene model can be used to increase efficiency of a local grid without reverse power flow.

IV. CONCLUSION

We propose a new decentralized autonomous smart grid model involving adaptive trading agents which can sell and buy electric power in a local electric power network. We name the electric power network inter intelligent renewable energy network, i-Rene. Trading agents in the local grid manage the amount of electric power generated by PV or other renewable energies stored in batteries in their houses. The agents learn trading policies by maximizing their profits. On the basis of the proposed system, we evaluated its price formation and effectiveness of the adaptive trading method analytically. To model demand side management which can control the amount of electric power consumption, developing an elastic additional consumption model is essential. We added

an elastic additional consumption model to the model. We also performed a simulation experiment with a hundred agents and additional noise term for load profiles.

Simulation results showed that i-Rene also can work efficiently to some extent in environments including noisy consumption and generation. As a result, fluctuated price automatically organized in a bottom-up way in a market reduced demand in peak load time and increased demand in periods when they had enough electricity. Such elasticity in demand enabled agents to manage SOC profiles more efficiently, and they could make use of generated electricity in a better way.

In our future work, we should prove that our model can be applied to the real environment. The real environment includes unknown elasticity of demands, various structured random variables about consumption and generation profiles, and non-
white noise. Finding a way of treating them adequately in our model is also important.

The future electricity network cannot be built only with a material system but with flexible artificial intelligence and human adaptability. To overcome energy problems, autonomous artificial intelligence cooperating with human adaptability should contribute to providing a future smart grid.

**REFERENCES**


