A Multi-Objective Optimization Method on Consumer's Benefit in Peer-to-peer Energy Trading

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***Abstract*—In recent years, many countries have been promoting the shift from centralized energy systems to distributed ones for clean energy utilization. Direct energy trading among consumers has drawn increasing interest in the development of efficient utilization of distributed energy systems. However, a part of consumers might not be able to receive electricity from their preferred suppliers since some suppliers have limited capacity of supplying electricity. This occasion leads to a decrease in the consumer's benefit. Existing studies are mainly focused on not the equity of prosumer's benefit but the efficiency of resource allocation. Therefore, a mechanism that satisfies not only balance between supply and demand but market participants' preferences is required. In this paper, a multi-objective optimization problem as market mechanism is proposed to improve both the equity of consumer's benefit and the efficiency of resource allocation. For solving the proposed optimization problem, six Evolutionary Algorithms (EAs) are selected. Simulation results show that the selected EAs can be classified into two types: (i) algorithms optimizing both the efficiency of resource allocation and the equity of consumer's benefit and (ii) algorithms optimizing only one of the two objectives.**

***Keywords*–Peer-to-Peer Energy Trading; Evolutionary Algorithm; Multi-objective Optimization Problem; Graph Theory.**

I. Introduction

Many countries have been encouraging people to utilize distributed energy systems such as solar and wind power generations for environmental issues. Existing energy systems have been relying on fossil fuels heavily because this kind of energy systems can supply electricity to a great number of consumers with fewer electric outage. However, such energy systems emit a large amount of greenhouse gas, which leads to a factor contributing to global warming. Therefore, many countries have legislated policy to enhance the rate of renewable energy utilization.

One of the efforts of governments in many countries is to enact Feed-In Tariff (FIT), which aims at spreading renewable energy systems widely to general households. Consumers who own energy generators are called prosumers [1] because they do not only consume electricity but also produce it. FIT guarantees that public utilities purchase excess electricity from consumers at a fixed rate in a certain period. FIT leads consumers to be able to have the outlook for the return on installation costs of renewable energy systems. Therefore, renewable energy systems have drawn increasing interest in general households, and the number of prosumers has been increasing year by year.

For efficient excess electricity utilization, energy market frameworks have been proposed by governments in many countries. For example in Japan, one of the methods is Virtual Power Plant (VPP) that aggregates capacities of heterogeneous distributed energy resources. Another example is Demand Response (DR) which is a change in consumption of consumers to match demand for electricity with supply. In VPP and DR, there are aggregators who join a local energy market as third party to manage prosumer's energy resources. However, in these methods, transparency of trading is unclear, and an intermediate margin is incurred due to a third party such as an aggregator.

In order to cope with the issues described above, direct energy trading among consumers and prosumers that is regarded as Peer-to-Peer (P2P) energy trading has been gathering attention. Fig. 1 represents present energy trading, and Fig. 2 shows P2P energy trading. As shown in Fig. 1, consumers can trade electricity with the only one public utility in present energy trading. On the other hand, as shown in Fig. 2, consumers can trade electricity with not only the public utility but other consumers in P2P energy trading. Energy trading without a third party is expected to increase transparency of trading and reduce electricity rates. P2P energy trading would make consumers motivated to exchange electricity with others, and efficient electricity utilization in a local energy market will be realized. Nowadays, the feasibility of P2P energy trading will improve with the advent of blockchain technology.

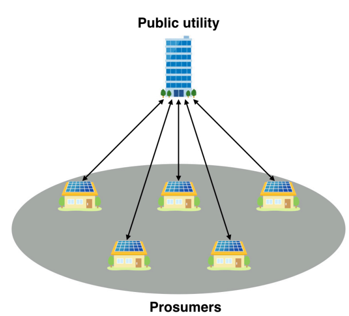

Fig 1. Present energy trading.

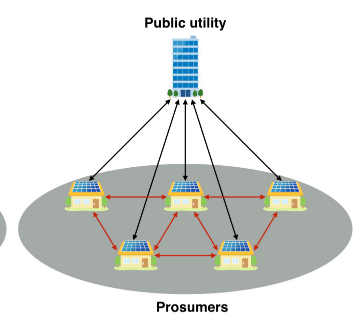

Fig 2. Peer-to-peer energy trading.

However, if P2P energy trading is implemented in practical markets, a couple of issues might occur due to market constraints. In P2P energy trading, candidates for consumer's trading partner will be diversified, and each consumer will have preferences for market participants. Consumers will decide their trading partners based on their preferences. There is a special constraint that must meet supply and demand for electricity in energy markets. If each market participant acts to maximize their benefit in markets and decides their trading partner arbitrarily, balance between supply and demand for electricity might collapse because of breaking the market constraints. Furthermore, if each market participant decides their trading partners under the market constraints, some consumers might not be able to trade electricity with their desirable partners since prosumers have limited capacity of supplying electricity. These occasions lead to a decrease in the consumer's benefit. Therefore, a mechanism that satisfies not only balance between supply and demand but market participant's preference is required.

For P2P energy trading realization, many studies have been conducted to consider P2P trading models. Jiawen *et al.* propose an auction mechanism that determines optimal electricity rates and the amount of electricity traded between sellers and buyers in an electric vehicle market in [2]. In [3], Muhammad *et al.* present a smart home model for minimizing the total of payment to the public utility and eliminating inequalities of energy. Pourya *et al.* formulate an economic dispatch problem for reducing operation costs in a community microgrid in [4]. Yue *et al.* evaluate some P2P energy sharing mechanisms based on multi-agent simulation frameworks that might bring both economic and technical benefit in [5]. Chao *et al.* present a two-stage aggregated control for maximizing economic benefit of each prosumer in [6]. In [7], Wayes *et al.* present a price discrimination method that is able to conduct envy-free energy trading and to maximize the total of consumer's benefit. These studies described above analyze not the equity of consumer's benefit but only the efficiency of resource allocation in P2P trading markets.

Therefore, our study proposes a P2P energy trading model and analyzes trading focusing on each consumer's benefit besides an overall market. In P2P trading, consumer's production and demand vary over time, and their benefit is anticipated changing complicatedly. Our model is denoted by Time-Varying Graph (TVG) [8] to represent time-varying consumer's behavior. Furthermore, a multi-objective optimization problem as market mechanism is formulated to investigate benefit of each consumer. Since P2P energy trading has not been applied to a practical market, electricity trading should be investigated more carefully.

This paper is structured as follows. Section II explains the definitions of our energy trading model with a time-varying graph. Section III formulates a multi-objective optimization problem and demonstrates the simulation results. Section IV concludes this paper and expresses future works.

II. Model representation

This section introduces our P2P energy trading model by utilizing notation of graph theory. An optimization problem is formulated to investigate P2P energy trading.

A. P2P energy trading model as graphs

Our electricity market model is composed of two kinds of participants that are a public utility and consumers. The set of all participants is expressed by V. Public utility is denoted by $v_p \in V$. Since energy trading among only consumers will not be able to provide for all demand, it is assumed that there is a public utility in our model for covering all electricity deficit and excess electricity. Consumer is represented by $v_i \in V(i = 1, 2, \ldots, |N|)$ and varies its behavior between seller and buyer according to time. If a consumer has excess electricity, the consumer can be seller. On the other hand, if a consumer runs out of generated electricity, the consumer can be buyer. Some consumers might not have own energy generators, and their production should be set to zero in this case. $V_S \subset V$ indicates the set of consumers who are sellers, and $V_B \subset V$ expresses the set of consumers who are buyers.

Consumer v_i changes its behavior depending on its production and consumption of electricity in P2P trading markets. Consumers must trade electricity during time span $\mathcal{T}$. Consumer's production and consumption at each time $t \in \mathcal{T}$ are represented by $p_i^t \in \mathbb{R}$ and $c_i^t \in \mathbb{R}$ respectively. If $p_i^t > c_i^t$, v_i will be seller and can supply electricity to other participants. Conversely, if $p_i^t < c_i^t$, v_i will be buyer and can purchase electricity from other participants. Furthermore, if $p_i^t = c_i^t$, v_i will be neither seller or buyer and does nothing in markets at t.

In order to model a P2P trading market considering time-varying consumer's behavior, TVG is utilized. A P2P trading model at each time is represented by TVG that consists of four types of vertices: the white vertices behaving as sellers, the black vertices behaving as buyers, the gray vertex doing nothing in the markets, and the blue vertices expressing public utilities. The set of arcs is denoted by A, and each arc of TVG at t is represented by $(v_i, v_j) \in A^t$. Arc (v_i, v_j) expresses the relationship where v_j can purchase electricity with v_i. Each arc must connect two vertices. The direction of the arrows represents electricity flow. TVG in Fig. 3 is expressed as $\mathcal{G} = (V, A, \mathcal{T})$. By using this model, consumer's benefit can be investigated in detail at each time.

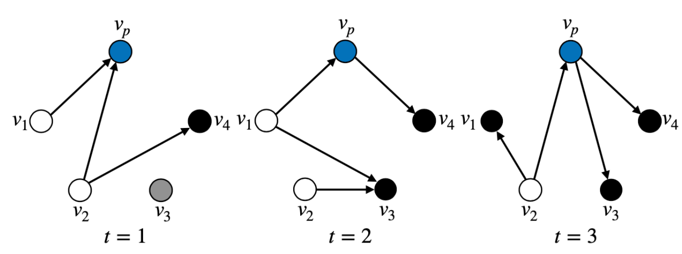

Fig 3. Time-Varying Graph $\mathcal{G}$.

An underlying graph indicates relationships among market participants where they can trade electricity with each other over a trading period as a sort of footprints of TVG. Fig. 4 that consists of the blue vertices expressing a public utility and the orange vertices representing consumers is represented by an underlying graph of $\mathcal{G}$ in Fig. 3. The set of edges is denoted by E, and each edge of the underlying graph is represented by $(v_i, v_j) \in E$. Edge (v_i, v_j) denotes the relationship where v_j can purchase electricity from v_i. Underlying graph in Fig.

4 is expressed by $G = (V, E)$. Since an underlying graph is finalized by aggregating TVG, the cumulative benefit of each consumer can be analyzed in this model.

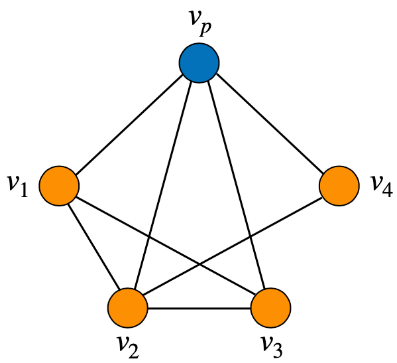

Fig 4. An underlying graph G.

B. Constraints of trading volume

Each consumer has capacity of supplying and purchasing electricity depending on its production and consumption. The amount of electricity traded between v_i and v_j is represented by $x\colon (V_S \cup \{v_p\}) \times (V_B \cup \{v_p\}) \to \mathbb{R}$, and x is called trading volume. Each arc $(v_i, v_j) \in A^t$ has capacity where v_i can supply electricity to v_j up to the maximum trading volume. Capacity of $(v_i, v_j) \in A^t$ is denoted by the function cap : $(V_S \cup \{v_p\}) \times (V_B \cup \{v_p\}) \times \mathcal{T} \to \mathbb{R}$. The trading volume on each arc must satisfy the following constraints:

$$0 \leq x^t (v_i, v_j) \leq cap^t (v_i, v_j) \quad (v_i \in V_S, v_j \in V_B, t \in \mathcal{T}), \tag{1}$$

$$0 \leq x^t (v_i, v_p) \leq cap^t (v_i, v_p) \quad (v_i \in V_S, t \in \mathcal{T}), \tag{2}$$

$$0 \leq x^t (v_p, v_j) \leq cap^t (v_p, v_j) \quad (v_j \in V_B, t \in \mathcal{T}). \tag{3}$$

Funcion cap is calculated by different formulae depending on trading pairs. Excess electricity of seller v_i is defined as $p_i^t - c_i^t$, and electricity deficit of buyer v_j is defined as $c_j^t - p_j^t$. If both v_i and v_j are prosumers, capacity of (v_i, v_j) at t is set as

$$cap^t (v_i, v_j) = \min \left(\left(p_i^t - c_i^t\right), \left(c_j^t - p_j^t\right) \right).$$

Since a public utility covers all consumer's electricity deficit, it is assumed that the public utility can supply electricity to all consumers. Therefore, capacity of (v_p, v_j) at t is defined as

$$cap^t (v_p, v_j) = c_j^t - p_j^t.$$

Moreover, since the public utility covers all consumer's excess electricity, it is assumed that the public utility can purchase electricity from all consumers. Therefore, capacity of (v_i, v_p) at t is defined as

$$cap^t (v_i, v_p) = p_i^t - c_i^t.$$

Sellers must sell electricity which is equal to the amount of own excess electricity to others. Buyers must purchase electricity which is equal to the amount of own electricity deficit from others. The above constraints are expressed by

$$\sum_{v_j \in V_B \cup \{v_p\}} x^t(v_i, v_j) = p_i^t - c_i^t \quad (v_i \in V_S, t \in \mathcal{T}), \tag{4}$$

$$\sum_{v_i \in V_S \cup \{v_p\}} x^t(v_i, v_j) = c_j^t - p_j^t \quad (v_j \in V_B, t \in \mathcal{T}). \tag{5}$$

C. Rate

Consumers behaving as seller and a public utility have rates when dealing with their electricity. Seller $v_i \in V_S$ offers the unit of electricity with rate $r_i \in \mathbb{R}$ to buyers $v_i \in V_B$. When v_i supplies electricity $x^t(v_i, v_j)$ to v_j, v_j must purchase electricity at $x^t(v_i, v_j) \cdot r_i$ from v_i. Public utility v_p offers the unit of electricity to buyers with rate $r_s \in \mathbb{R}$, where it is assumed that $r_s \geq r_i$. When v_p supplies electricity $x^t(v_p, v_j)$ to v_j, v_j must purchase electricity at $x^t(v_p, v_j) \cdot r_s$ from v_p. Public utility v_p purchases electricity at rate $r_b \in \mathbb{R}$ from sellers, where it is assumed that $r_i \geq r_b$. When v_i supplies electricity $x^t(v_i, v_p)$ to v_p, v_p must purchase electricity at $x^t(v_i, v_p) \cdot r_b$ from v_i.

D. Reservation price

Each consumer has a reservation price in energy trading. The reservation price of buyers is the maximum price where buyers can purchase electricity from others. Conversely, the reservation price of sellers is the minimum price where sellers can supply electricity to others. The reservation prices of consumers are represented by the function $\omega\colon V \times \mathcal{T} \to \mathbb{R}$. ω is calculated from different formulae depending on consumer's behavior. Thus, the reservation prices are expressed by the following formulae:

$$\omega^t (v_i) = \begin{cases} (p_i^t - c_i^t) \cdot r_b & (p_i^t > c_i^t), \\ (c_i^t - p_i^t) \cdot r_s & (p_i^t < c_i^t). \end{cases}$$

Since each consumer must deal electricity with the only public utility in present electricity trading, $\omega^t(v_i)$ is set as a price offered by the public utility in this paper.

E. Consumer's benefit

Consumers can benefit from trading when they trade electricity with more favorable partners than current ones. Consumer's benefit is represented by the function $\pi\colon V \to \mathbb{R}$. π is also calculated from different formulae depending on consumer's behavior. Seller's benefit is defined as the difference between the total income and the reservation price of sellers. Consumer's income is represented by the function $\zeta\colon V_s \times V_b \times \mathcal{T} \to \mathbb{R}$. The total of each seller's income is defined as

$$\zeta^t (v_i) = \sum_{v_j \in V_B} x^t (v_i, v_j) \cdot r_i + x^t (v_p, v_i) \cdot r_s.$$

If a consumer behaves as seller, consumer's benefit is defined as

$$\pi^t (v_i) = \zeta^t (v_i) - \omega^t (v_i).$$

Conversely, buyer's benefit is defined as the difference between the reservation price of buyers and the total of expenditure. Consumer's expenditure is represented by the function $\eta\colon V_s \times V_b \times \mathcal{T} \to \mathbb{R}$. The total of buyer's expenditure is defined as

$$\eta^t (v_j) = \sum_{v_i \in V_S} x^t (v_i, v_j) \cdot r_i + x^t (v_p, v_j) \cdot r_s.$$

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If a consumer behaves as buyer, buyer's benefit is defined as

$$\pi^t(v_j) = \omega^t(v_j) - \eta^t(v_j).$$

Since all of the consumers must not suffer from monetary deficits caused by electricity trading in our model, it is assumed that $\pi^t(v_i) \geq 0$, $\pi^t(v_j) \geq 0$. This research focuses on P2P trading in one local energy market, that is, a public utility will be negligibly affected by energy trading. Therefore, public utility's benefit is not considered.

F. Problem formulation

In order to investigate consumer's benefit, a multi-objective optimization problem is formulated. One of the objectives is to maximize the total of consumer's benefit. The other objective is to minimize the standard deviation of consumer's benefit. This problem is expected to obtain solutions with the high efficiency of resource allocation and the high equity of prosumer's benefit. The problem is defined as follows.

$$\begin{aligned} \text{maximize} \quad & \sum_{v_i \in V_S \cup V_B} \pi^t(v_i). \\ \text{minimize} \quad & \sqrt{\frac{\sum_{v_i \in V_S \cup V_B} (\overline{\pi} - \pi^t(v_i))^2}{|N|}}. \\ \text{subject to} \quad & (1), (2), (3), (4), \text{and } (5), \end{aligned}$$

where the objective functions are optimized at each time t.

Constraints (1), (2), and (3) indicate that the amount of electricity traded between participants on each arc is less than or equal to capacity of each arc. These constraints also show that the amount of electricity traded between participants is not a negative value. Constraint (4) represents that the total of seller's trading volume is equal to the amount of own excess electricity, and constraint (5) expresses that the total of buyer's trading volume is equal to the amount of own electricity deficit.

III. EXPERIMENTAL RESULTS

To obtain solutions optimized by the multi-objective optimization problem, a simulator is developed with Platypus [9] that is a framework for evolutionary computing in Python. The following six selected Evolutionary Algorithms (EAs) as metaheuristics methods are utilized in our simulation.

- Non-dominated Sorting Genetic Algorithms-I I (NSGA-II)
- Generalized Differential Evolution-III (GDE3)
- Optimized MultiObjective Particle Swarm Optimization (OMOPSO)
- Speed-constrained Multiobjective Particle Swarm Optimization (SMPSO)
- Strength Pareto Evolutionary Algorithm-II (SPEA2)
- ϵ-MultiObjective Evolutionary Algorithm (ϵ-MOEA)

The reason for utilizing metaheuristics algorithms is that they are expected to be able to apply for an expanded market with a large number of participants.

A. Conditions

In our simulation, parameters were determined in reference to the electricity market in Japan. The public utility supplies electricity to consumers at 29.05 yen per kWh and purchases electricity from consumers at 8.05 yen per kWh. Consumers supply electricity to other consumers at 18.55 yen per kWh, it comes from the average between the public utility's offering rate and purchasing rate. Seller's production p_i and consumption c_i are set to 549 Wh and 502 Wh respectively. Buyer's production p_i and consumption c_i are set to 455 Wh and 502 Wh respectively. The number of iterations is set to 1,000. Since the optimization problem was solved every one hour for deciding trading partners, trading for 1000 hours was determined in the experiments. In each round of simulations, the number of samples is set to 10000, and the population is set to 100. For OMOPSO and ϵ-MOEA, ϵ is set to 0.05.

With the assumed market, a simulation was conducted with each of the following four patterns:

- 3 sellers and 0 buyer (Pattern 1)
- 2 sellers and 1 buyer (Pattern 2)
- 1 seller and 2 buyers (Pattern 3)
- 0 seller and 3 buyers (Pattern 4)

B. Results and discussion

In Pattern 1 and Pattern 4, there is only one kind of solutions that both the total of consumer's benefit and the standard deviation are zero in all selected EAs. This paper introduces only the results of Pattern 2 because the results of Pattern 3 have a tendency similar to Pattern 2. Since EAs obtained Pareto solutions, this research randomly extracted one of the Pareto solutions at each time.

Fig. 5 depicts the solutions obtained by NSGA-II in Pattern 2. The results of SMPSO, SPEA2 and ϵ-MOEA have a tendency similar to NSGA-II. In Fig. 5, the horizontal axis depicts the total of consumer's benefit, and the vertical axis shows the standard deviation of consumer's benefit. Simulation results show that NSGA-II discovered various kinds of solutions under the same conditions. Figs. 6 and 7 show each of the two objective functions at each time in Fig. 5. In Fig. 6, the horizontal axis depicts t, and the vertical axis shows the total of consumer's benefit. In Fig. 7, the horizontal axis depicts t, and the vertical axis shows the standard deviation of consumer's benefit. These results show that the solutions are dense toward the optimal area, and NSGA-II tended to find solutions on the Pareto front. As shown from the results, NSGA-II facilitates deciding ideal trading depending on methods to select solutions.

Fig. 8 represents the solutions obtained by OMOPSO in Pattern 2. The results of GDE3 have a tendency similar to OMOPSO. The horizontal and vertical axes in Fig. 8 depict the same as Fig. 5. Simulation results show that OMOPSO found solutions optimized for only one of the two objective functions in most cases. Figs. 9 and 10 show each of the two objective functions at each time in Fig. 8. The horizontal and vertical axes in Fig. 9 depict the same as Fig. 6, and the horizontal and vertical axes in Fig. 10 represent the same as Fig. 7. As shown in Fig. 9, the solutions are dense in the

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upper part and the lower part of the figure. The solutions in the upper part show the maximum total of consumer's benefit. On the other hand, the solutions in the lower part show that all consumers could not obtain benefit at that time. Fig. 10 also shows that the solutions are dense in the upper part and the lower part of the figure. The solutions in the lower part show that the variation in consumer's benefit is zero, that is, they are the best solutions in terms of the equity of consumer's benefit. On the other hand, the solutions in the upper part show that consumer's benefit with the low equity is obtained. As shown from the results, when only one objective function is optimized, the other objective function is likely to be inferior in this algorithm.

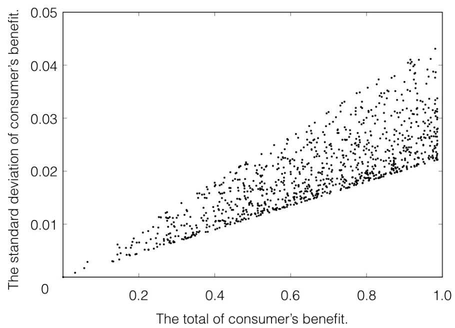

Fig 5. Solutions obtained by NSGA-II in Pattern 2.

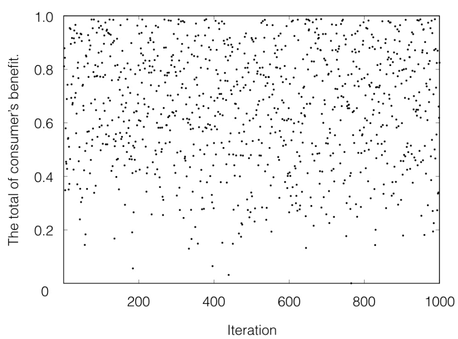

Fig 6. Total of consumer's benefit obtained by NSGA-II.

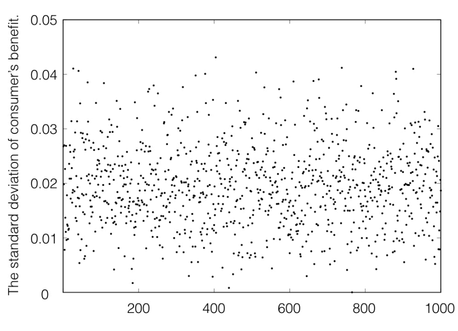

Fig 7. Standard deviation obtained by NSGA-II.

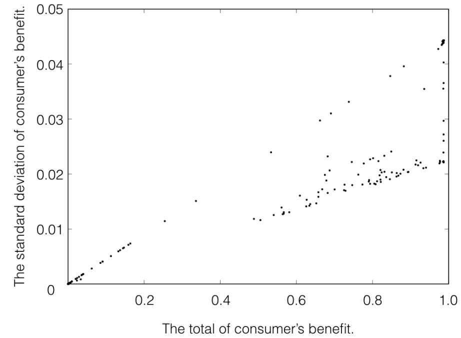

Fig 8. Solutions obtained by OMOPSO in Pattern 2.

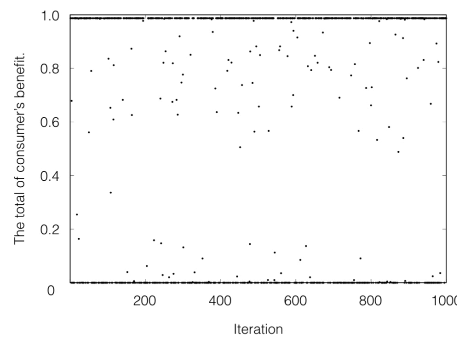

Fig 9. Total of consumer's benefit obtained by OMOPSO.

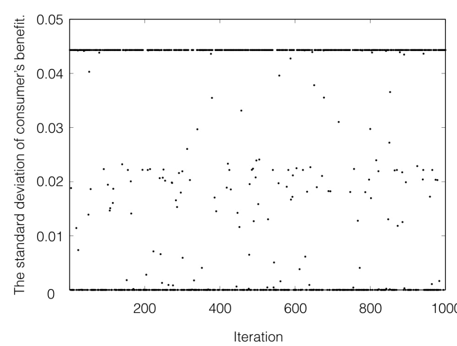

Fig 10. Standard deviation obtained by OMOPSO.

IV. CONCLUSION AND FUTURE WORK

This research proposed the P2P trading model with time-varying consumer's behavior and the multi-objective optimization problem was formulated to investigate consumer's benefit. Simulation results show that OMOPSO and GDE3 tended to find solutions optimized for only one of the two objective functions, and the other algorithms such as NSGA-I I, SMPSO, SPEA2 and ϵ-MOEA tended to discover solutions dense on the Pareto front. As shown from the results, NSGA-II, SMPSO, SPEA2 and ϵ-MOEA facilitate deciding ideal trading depending on methods to select solutions. As future work, a method to select solutions obtained by the multi-objective optimization problem should be considered to allocate energy that consumers can obtain benefit equitably.

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