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Impact of Retailer and Consumer Behavior on Voltage in Distribution Network Under Liberalization of Electricity Retail Market

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SUMMARY

The liberalization movement in Japan will be expanded to the residential sector and full liberalization of the retail market will be achieved in the near future. Against this background, it is expected that transactions in a distribution network (DN), which has many consumers of the residential sector, will be activated. Furthermore, consumers can control their loads depending on the selling prices offered by retailers with the introduction of demand response (DR) technologies such as home energy management systems (HEMS). Due to the variation of load by DR, however, the voltage profile in DN may be changed compared to the present situation. This may make voltage management difficult and cause problems such as voltage deviation from an adequate range. In this paper, the impact of DR in a liberalized electricity market on DN is evaluated for efficient voltage management. In order to evaluate the behavior of the retailer and consumers, this paper proposes a bi-level programming approach based on the Stackelberg game model. Solving the bi-level programming problem including the power flow equation for a DN model based on the IEEE 13-bus test feeder, we analyze the impact of the retailer and consumers on the voltage in the DN in order to account for transactions between these market players.

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Key words: electricity liberalization; demand response; marketing; distribution network; voltage management.

1. Introduction

According to the Revised Electricity Business Act, which mandates reforms of electricity systems in three phases, complete deregulation of the power retail market is scheduled for 2016. Thus, power retail transactions that were previously allowed for some large-scale consumers will be available to consumers in the residential sector and other regulated sectors. As a result, we may expect power wheeling services provided by retail operators via distribution networks (DNs) owned by power distribution companies (DisCo). In addition, considering the power supply risks that have become obvious after the Great East Japan Earthquake, the efficiency of demand response (DR) is attracting attention in Japan. This includes peak cuts due to energy-saving efforts on the consumer side. In addition, verification tests are being conducted throughout the country with systems offering efficient energy management such as HEMS (Home Energy Management System) and BEMS (Building Energy Management System) [1, 2]. With progress in HEMS, BEMS, and other DR-related technologies, consumers will be able to more flexibly control power consumption [3, 4], which offers higher elasticity of consumer prices. On the other hand, in the liberalized market, transaction prices involving uncertain fluctuations [5–8] will cause load fluctuations related to varying electricity rates [9], and hence we may expect voltage fluctuations in power DNs. In particular, the residential loads to be deregulated are connected to DNs, and the influence of retail liberalization on the system voltage would not necessarily be small.

The power distribution divisions of power companies perform proper voltage management by maintaining the voltage distribution in power lines based on contract volumes, past consumption data, and so on. However, as mentioned above, voltage profiles in DNs may change with complete retail deregulation, and therefore, the effects of retail deregulation and DR on the system voltage must be sufficiently examined for proper voltage management. Many past studies were devoted to the behavior of decision makers in the electricity market such as ISOs (Independent System Operators), generating companies, or consumers. Specifically, those studies analyzed pricing processes [10, 11], the problem of optimal energy procurement

[7, 8, 12–14], the relaxation of distribution line congestion using LMP (Locational Marginal Price) [15], and other issues; however, to the best of our knowledge, evaluation in terms of voltage has been far from sufficient.

To analyze the effects of DR on DN voltages with electricity liberalization, we must clarify the market behaviors of decision-makers such as consumers and retailers. There are examples of consumer modeling based on price plasticity [6]; however, it is difficult to reproduce rational behavior of consumers with an analysis using price plasticity in the case of the transaction structure considered in this study, that is, a DR based on electricity rate setting by retail operators, and rational decisions made by consumers according to these rates. Transactions among retailers, generators, and consumers in the power market can be naturally modeled as a Stackelberg game, assuming that every decision-maker acts optimally. This is formulated as a bi-level programming problem [13, 14, 16]. The Stackelberg game model involves two decision-makers; first, a high-level decision-maker adopts a strategy, and then a low-level decision-maker adopts his own strategy under the condition that the strategy of the high-level decision-maker can be known [17]. The purpose of the present study is the formulation of transactions between retailers and consumers as a bi-level programming problem. Thus, we aim at predicting the behaviors of retailers and consumers in a completely deregulated market, and at clarifying the impact of such behaviors on the DN voltage.

The paper is organized as follows. In Section 2, we model retail transactions in a DN by formulating and solving a bi-level programming problem with two decision-makers, namely, a retailer and a consumer. In Section 3, we explain the simulation conditions, and then in Section 4 we analyze the behaviors of retailers and consumers under retail liberalization with respect to DR penetration, and discuss the results obtained by simulation of the impact of retailers and consumers on the DN voltage. Finally, results of this study are summarized in Section 5.

2. Formulation

2.1 Retailer model

Multiple decision-makers, namely, generating companies (GenCo), transmitting companies (TransCo), distributing companies (DisCo), and retailers, participate in a liberalized market. The decision-makers are involved in various transactions such as forward trading and premarket trading, or day-ahead trading (spot market). In this paper, we consider only power DNs, and, like Zugno and colleagues [16], we assume a model in which retailers procure electric power in the market and supply it to consumers connected to a DN. Therefore, we leave aside the influence of GenCo bidding and TransCo wheeling charges, and so on, on electricity tariffs and consider retail transactions between retailers and consumers in a DN.

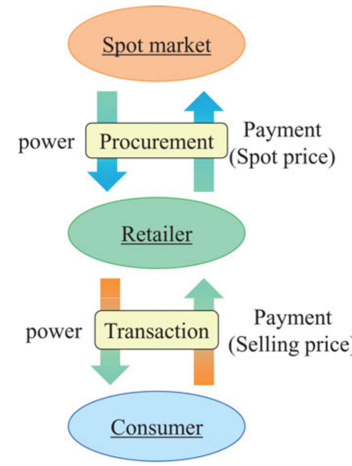

Fig. 1. Transaction model. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

With the separation of generation, transmission, and distribution due to market deregulation, the DisCo supplies consumers with electric power procured in the market, while maintaining the DN voltage within a proper range [14]. Usually, the DisCo and retailer are different entities in a power market. However, it has been pointed out that both can be treated in a same way in terms of "maximizing profit under DN constraints (voltage, etc.)," because the DisCo is assumed to make efforts toward reduction of network management costs [7, 14]. In a number of previous studies [7, 8, 12–15], the DisCo and retailer have been considered as the same, with regard to various constraints of power systems (line capacity, voltage, and so on). Under this assumption, the retailer's decisions are affected by system operating constraints; thus, in this study, the retailers set electricity rates with regard to the voltage management cost. With market liberalization, we may expect competition among retail operators [14]; however, in this investigation, like Zugno and colleagues [16], we simplify the problem by assuming that a single retailer supplies electric power to consumers within a DN, and impose constraints on electricity rates in order to model competition among retailers.

Retailers purchase electric power on the spot market and set rates to maximize profit, as shown in Fig. 1. Based on the rates, consumers determine the amount of electricity to buy from retailers. Transactions made by retailers in the power market may include forward trading and premarket trading as well as real-time transactions [6–8]; in this study, we assume that retailers procure power on a large-volume spot market and make a profit by selling power to consumers at a price including some commission [16].

When setting tariffs, retailers consider not only the power consumed by consumers, but also the costs of distribution line loss, voltage management, and so on.

2.2 Consumer model

With the proliferation of HEMS, BEMS, and so on, consumers are assumed to be capable of DR with respect to electricity rates [3, 14, 15]. When power consumption is reduced due to DR, the consumers can reduce their power purchase cost; on the other hand, this results in a number of disutilities such as loss of convenience (restrictions on the use of electric appliances), and a decreased customer attraction rate for commercial loads or decreased productivity for industrial loads. Thus, based on the Stackelberg game model, we assume that consumers determine their energy consumption rationally, with regard to the utilities resulting from power purchase and the disutilities resulting from reduction of power consumption, in order to minimize the total of power purchase cost and disutilities related to the underconsumption of electricity. The actual behavior of consumers is not necessarily rational; however, the concept of ADR (automated DR) [21], involving optimal (rational) variation of power consumption according to preset conditions, has been attracting considerable attention, and we assume that consumers will become capable of rational behavior with the introduction of such information and of communication systems and technologies. In addition, consumers have both controllable and uncontrollable loads. Here we assume that DR involves only controllable loads. There are consumer models based on price elasticity [6], but in this case it would be difficult to analyze consumer decisions affected by factors other than air temperature (in the case of air conditioning) or electricity rates; thus, we use disutilities for modeling in this study.

Since consumers may have different preferences, in this paper we assume three types of consumers, namely, residential, commercial, and industrial loads. In the case of commercial and industrial loads, reduction of power consumption often causes disutilities; however, commercial and industrial loads with heavy power consumption suffer from high power purchase costs, and it is possible to think of efficient incentives for introducing BEMS and other means to reduce power purchase cost. Thus, in this study we assume that commercial and industrial loads are also involved in DR. The breakdown of consumers by type is different for each power DN; here we assume that residential, commercial, and industrial loads have equal shares (1/3 each) in order to examine how the voltage is affected by differences in consumer preferences. For each load type, we set a desired demand using typical demand patterns (24 h at 30-min intervals) in Japan under the existing electricity rate scheme [22]. The consumers determine their energy consumption based on the desired demand and electricity rates. Information about rates is assumed to be provided by retailers. For simplicity, we assume that all consumers of one type have the same power consumption patterns.

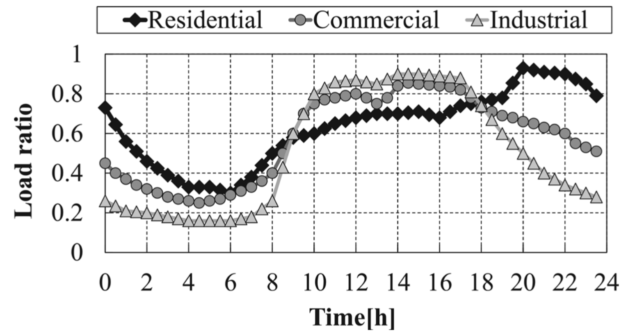

Fig. 2. Ideal load data.

Figure 2 shows how the ratio of desired demand to load capacity varies hourly for every consumer type. For residential loads, the demand is high from evening to night, then decreases in the morning, which is much different from commercial and industrial loads. In the case of shops, office buildings and other commercial loads, demand is highest in daytime (working hours); for industrial loads, too, demand is highest during day-time hours when production facilities are in operation. Although the present electricity rate scheme includes some time-of-day rate provisions, DR systems have not been sufficiently introduced on the consumer side, and the desired demand can be considered equal to the actual load curves. We assumed that the load power factor does not change with time, and that the consumer's reactive power varies directly with power consumption. The desired demand shown in Fig. 2 represents summer load patterns when the load is high; summer is chosen as the season in which DR has the greatest impact on the DN voltage. We may assume that the consumer's disutility due to underconsumption of electricity depends on a sense of discomfort stemming from reduction of air conditioning or lighting in residential loads, and from a decline in the customer attraction rate or in productivity in commercial and industrial loads. According to Marco and colleagues [16], the disutility increases with the difference between the actual air temperature and the comfortable (desired) temperature controlled by air conditioning. The utility of electric power is high during periods of high desired demand, which causes a strong disutility in case of underconsumption; thus, in this study we assume that the disutility related to underconsumption of electricity is proportional to the desired demand shown in Fig. 2.

2.3 The bi-level programming problem

Decision making by retailers and consumers in the power market can be formulated as a bi-level programming

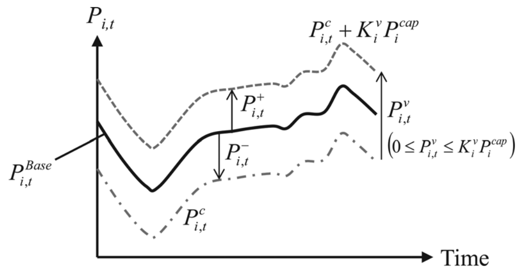

Fig. 3. DR of consumers.

problem [13, 14, 16]. In the high-level problem, the decision maker is a retailer aiming to maximize profit with regard to the response of the low-level decision makers (consumers) to electricity rates. Here, the decision variable is the electricity price λ_t^{sell}, $t = 0, 0.5, \ldots, 24$ set every 30 min by the retailer. That is, the electricity price is set for 24 h at intervals of 30 min. In the low-level problem, assuming rational behavior of the consumer (the decision-maker), the purpose is to minimize the total of power purchase cost and disutility related to underconsumption of electricity. Here the decision variable is the consumed energy $P_{i,t}^{+}$ exceeding the desired demand in Fig. 3. The bi-level programming problem is formulated as follows:

$$\text{maximize} \sum_{t\in T} \left\{ \lambda_t^{sell} \sum_{i\in N} P_{i,t} - \lambda_t^{spot} \left(\sum_{i\in N} P_{i,t} + P_{loss,t} \right) \right\} - C_{Tra} N_{Tra} \tag{1}$$

$$\text{subject to } \lambda_{min}^{spot} \le \lambda_t^{sell} \le K^U \lambda_{max}^{spot}, \forall t \in T \tag{2}$$

$$\lambda_{min}^{spot} = \min_{t\in T} \left(\lambda_t^{spot} \right) \tag{3}$$

$$\lambda_{max}^{spot} = \max_{t\in T} \left(\lambda_t^{spot} \right) \tag{4}$$

$$\sum_{t\in T} \lambda_t^{sell} = K_{profit} \sum_{t\in T} \lambda_t^{spot} \tag{5}$$

$$\mathbf{g_t}(\mathbf{P_t}, \mathbf{Q_t}) = \mathbf{0}, \forall t \in T \tag{6}$$

$$P_{loss,t} = f\left(V_{j,t}, \theta_{j,t} \right), \quad \forall j \in N_{node}, \forall t \in T \tag{7}$$

$$V_{min} \le V_{j,t} \le V_{max}, \quad \forall j \in N_{node}, \forall t \in T \tag{8}$$

$$\text{minimize} \sum_{t\in T} \left(\lambda_t^{sell} P_{i,t} + \rho_{i,t} P_{i,t}^{-} \right) \tag{9}$$

$$\text{subject to } i = N_{re} \tag{10}$$

$$P_{i,t} = P_{i,t}^{c} + P_{i,t}^{v} = P_{i,t}^{Base} + P_{i,t}^{+} - P_{i,t}^{-}, \forall t \in T \tag{11}$$

$$P_{i,t} \le P_i^{cap}, \forall t \in T \tag{12}$$

$$0 \le P_{i,t}^{+} \le K_i^v P_i^{cap}, \forall t \in T \tag{13}$$

$$0 \le P_{i,t}^{-} \le K_i^v P_i^{cap}, \forall t \in T \tag{14}$$

$$\sum_{t\in T} P_{i,t} = \sum_{t\in T} P_{i,t}^{Base}, \forall t \in T \tag{15}$$

$$\text{minimize} \sum_{t\in T} \left(\lambda_t^{sell} P_{i,t} + \rho_{i,t} P_{i,t}^{-} \right) \tag{16}$$

$$\text{subject to } i = N_{co} \tag{17}$$

(11)~(15)

$$\text{minimize} \sum_{t\in T} \left(\lambda_t^{sell} P_{i,t} + \rho_{i,t} P_{i,t}^{-} \right) \tag{18}$$

$$\text{subject to } i = N_{in}. \tag{19}$$

(11)~(15), where

[sets]

T is the time set $T = \{0, 0.5, \ldots, 23.5\}$

N is the consumer set $N = \left\{ N_{re}, N_{co}, N_{in} \right\}$

N_{re} is the residential load set

N_{co} is the commercial load set

N_{in} is the industrial load set

N_{node} is the DN node set

[indices]

t is the time (h)

i is the consumer

j is the DN node

[decision variables]

λ_t^{sell} is the electricity rate at time t (¥/kWh)

$P_{i,t}^{+}$ is the consumed energy exceeding the desired demand of consumer i at time t (kWh)

$P_{i,t}^{-}$ is the consumed energy below the desired demand of consumer i at time t (kWh)

[parameters]

λ_t^{spot} is the spot price at time t (¥/kWh)

K^U is the upper-limit coefficient for the electricity price

K_{profit} is the coefficient expressing the upper limit of the daily total electricity price

V_{max} is the upper limit of the proper voltage range (p.u.)

V_{min} is the lower limit of the proper voltage range (p.u.)

$P_{i,t}^{Base}$ is the desired demand of consumer i at time t (kWh)

P_i^{cap} is the maximum energy consumption per unit time determined by the load capacity of consumer i (kWh)

K_i^v is the controllable load coefficient of consumer i

$\rho_{i,t}$ is the disutility coefficient for underconsumption (with respect to the desired demand) of consumer i at time t (¥/kWh)

C_{Tra} is the cost of transformer operation at the distribution substation (¥/time)

[mapping]

f is the $(V_{j,t}, \theta_{j,t}) \rightarrow P_{loss,t}$ is the mapping from $V_{j,t}, \theta_{j,t}$ to $P_{loss,t}$

[dependent variables]

λ_{max}^{spot} is the maximum spot price (¥/kWh)

λ_{min}^{spot} is the minimum spot price (¥/kWh)

$V_{j,t}$ is the magnitude of the voltage at node $\#j$ at time t (p.u.)

$\theta_{j,t}$ is the phase of the voltage at node $\#j$ at time t (p.u.)

$P_{i,t}$ is the energy consumption of consumer i at time t (kWh)

$P_{loss,t}$ is the distribution line loss at time t (kWh)

$\mathbf{P}_t$ is the active power vector of the load at instant t

$\mathbf{Q}_t$ is the reactive power vector of the load at instant t

$P_{i,t}^{c}$ is the uncontrollable load of consumer i at time t (kWh)

$P_{i,t}^{v}$ is the uncontrollable load of consumer i at time t (kWh)

N_{Tra} is the number of operations of the transformer at distribution substation in 24 h (times)

[power flow equation]

$\mathbf{g_t}$ is the power flow equation vector at instant t

Equations (1) to (8) express the objective function and constraints of the high-level retailer. Equation (1) formulates the maximization of the retailer's profit as proceeds from the sale of power to the customers less the expenses of power procurement and voltage management cost. The energy procured by the retailer on the spot market is not necessarily equal to the energy actually consumed by the consumers; however, adjustment of the power balance in the hour-ahead market, and so on, is beyond the scope of this paper, and we assume for simplicity that the energy procured by the retailer on the spot market is equal to the sum of the energy consumption $P_{i,t}$ and the distribution line loss $P_{loss,t}$. In Eq. (1), N_{Tra} is the total number of transformer operations in 24 h, which depends on the voltage $V_{j,t}$ calculated from power flow Eq. (6). The voltage management cost is the product of the cost C_{Tra} per transformer operation in voltage control and the total number N_{Tra} of transformer operations in 24 h. Equation (2) represents the constraints on the upper and lower limits of electricity price set by the retailer. Generally, electricity rates decrease due to market competition; however, the rates are not likely to be considerably higher than the spot price, and the retailers would be unlikely to reduce the rates more than necessary. Thus, we impose an inequality constraint on the rates using the maximum and minimum spot prices $\lambda_{max}^{spot}, \lambda_{max}^{spot}$ defined by Eqs. (3) and (4) as shown in Fig. 4. Until complete retail liberalization, we will have no actual data on electricity prices determined by retailers; thus, in this investigation we applied the coefficient $K^U = 1.05$ of the maximum spot price to the upper limit of electricity rates, and set the lower limit of the rates equal to the minimum spot price. In order to model the reduction of the electricity price due to competition among retailers, Zugno and colleagues [16] imposed an inequality constraint so as to make the 24-h average electricity rate equal to the 24-h average spot price. In the present investigation too, λ_t^{sell} is constrained in Eq. (5) so as to reflect the market competition resulting in electricity rate reduction. However, in contrast to Zugno and colleagues [16], we take account of power distribution loss; thus, we set the 24-h average of λ_t^{sell} to the 24-h average spot price multiplied by K_{profit} in Eq. (5). K_{profit} is determined by $P_{loss,t}$ and market competition. In this investigation, we assume, for simplicity, that power is supplied by a single retailer. Thus, in order to simulate competition among retailers, we set $K_{profit} = 1.035$ so that retailer's profit is never negative but is not too large. In the high-level problem (Eqs. (1) to (8)), the objective function includes the distribution line loss $P_{loss,t}$ and the voltage management cost required to keep the voltage $V_{j,t}$ within its proper range. Thus, power flow Eq. (6) is introduced in order to calculate the physical quantities of the power DN such as $P_{loss,t}$ and $V_{j,t}$. For transactions on the electricity market, the dc power flow is often calculated for simplicity, which may degrade accuracy [14, 23]. In this investigation, we use the ac power flow equation for accurate voltage estimation. Using the solution $(V_{j,t}, \theta_{j,t})$ of the power flow equation, $P_{loss,t}$ can be found from Eq. (7). Equation (8) is a constraint expressing the maintenance the network voltage in the proper range using a transformer.

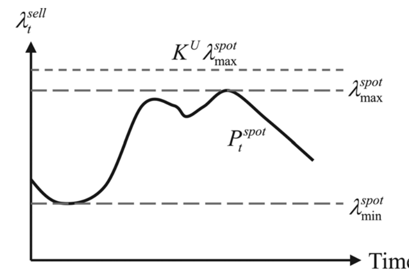

Fig. 4. Selling price determined by retailer.

In the low-level problem (Eqs. (9) to (15)), the objective function is set and minimized for each consumer type (residential, commercial, and industrial loads). Equation (9) is the objective function to minimize the sum of the power purchase cost and the disutility due to underconsumption caused by restrictions on power consumption. The minimization problem is formulated in Eqs. (9) to (15) for residential loads, in Eqs. (16), (17), and (11) to (15) for commercial loads, and in Eqs. (18), (19), and (11) to (15) for industrial loads. We assume that all consumers of one type have the same power consumption patterns; therefore the energy consumed by all consumers in the DN can be found by solving Eqs. (9), (16), and (18) under constraints (11) to (15). In particular, Eq. (11) expresses the energy consumption defined as the sum of the energy $P_{i,t}^{v}$ consumed by controllable loads and the energy $P_{i,t}^{c}$ consumed by uncontrollable loads (Fig. 3). However, the energy

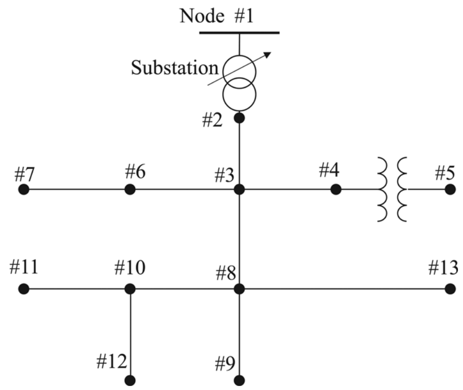

Fig. 5. Distribution network model.

consumption is limited by Pi^{cap}, and hence constraint (12) is imposed. Equations (13) and (14) are constraints on the consumer decision variables P_i^+ and P_i^-. The variables are restricted by the proportion K_i^v of controllable loads. With the introduction of HEMS, BEMS, and so on, consumers would be able to shift loads toward time slots with cheaper electricity rates [3, 4, 9, 15, 21]. and thus, in this paper we assume that the total daily energy consumption is made equal to the total desired demand due to such shifting, and we impose the corresponding constraint in Eq. (15).

By solving the above bi-level programming problem, we analyze the impact of consumers on the DN voltage in case of full-fledged retail liberalization. The retailer's optimization problem (1) to (8) includes nonlinear power flow Eq. (6), resulting in a nonlinear programming problem for which it is difficult to obtain exact solutions. In this investigation, Eqs. (1) to (8) are solved by PSO (Particle Swarm Optimization) [24], a metaheuristic method offering approximate solutions to nonlinear programming problems. The nonlinear power flow equation is calculated using the Newton-Raphson method, and the consumer's optimization problem (9) to (15) becomes a linear programming problem. Thus, we use the linear programming solver of MATLAB/Simulink.

3. Simulation Conditions

3.1 DN model

We simplified the IEEE 13-bus Test Feeder [25] to a three-phase balanced circuit and adjusted the loads and line impedance. The resulting system was used in the simulations as a DN model (Fig. 25). The detailed parameters of the DN model are given in the appendix. The numbers in Fig. 5 denote nodes; nodes #1 and #2 are, respectively, the primary and secondary sides of the distribution substation. A transformer is installed at the substation (between nodes #1 and #2), and the sending-end voltage can be controlled via its tap position. Because the transformer's tap changer is operated mechanically, the contacts are subject to wear during switching, thus shortening the device life [26]. The transformer's operation rate increases with the fluctuations of the network voltage, resulting in a higher voltage management cost (contact maintenance and so on). It seems appropriate to estimate C_{Tra} from the transformer's installation cost, service life, expected number of operations, and depreciation cost dictated by the DisCo maintenance cost. However, DisCo data are not available, and in this investigation we set $C_{Tra} = 200$ ¥/time so that the retailer's profit is never negative but not too large. Actually, the voltage at the primary side (power transmission system) of a distribution substation fluctuates depending on various factors, but the TransCo is assumed to maintain the voltage within a proper range. Thus, in this investigation, the voltage of node #1 (primary side) is fixed at 1.01 p.u., and voltage fluctuations caused by load fluctuations in the DN are compensated by the transformer installed between nodes #1 and #2.

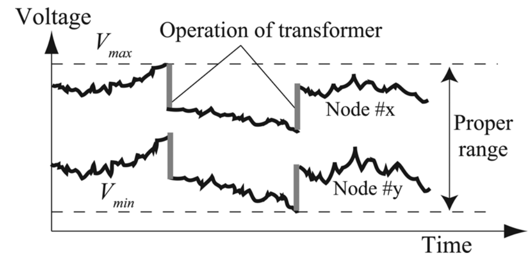

Fig. 6. Operation of transformer.

There are a number of methods for transformer control, such as LDC (line drop compensator) or keeping the secondary voltage within the dead zone, but consideration of such control methods is beyond the scope of this paper. Thus we assume that the transformer monitors the voltage in the DN (nodes #2, 3, ..., 13), and if the voltage at any of nodes #2, 3, ..., 13 deviates from its proper range (V_{max} to V_{min}), the transformer's tap is switched to keep the voltage within the range (Fig. 6). In this investigation, $V_{max} = 1.05$ p.u., $V_{min} = 0.95$ p.u., and the transformer's tap width is 0.0082 p.u. In addition, phase-advancing capacitors (SC) are connected at nodes #9 and #13 to improve the power factor. Because this study evaluates the impact of DR on the DN voltage, we assume that the SCs are not switched depending on load fluctuations, but are operated rather constantly.

3.2 Spot market model

The purpose of this investigation is not to consider the retailer's problem of power procurement with regard to uncertainties of the spot price and power consumption [6, 8], but rather to evaluate how retailers and consumers

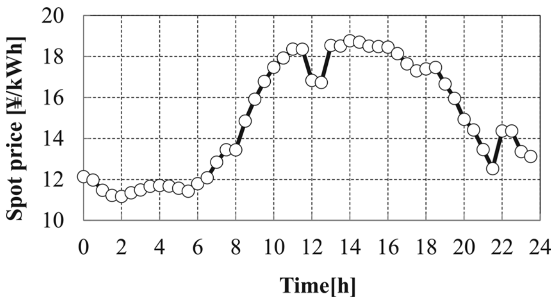

Fig. 7. Spot price.

affect the voltage in power DNs. Thus, we do not discuss bidding on the spot market or fluctuations of contract prices; instead we assume that spot prices are determined regardless of the retailer's behavior. In the numerical simulations, we set the spot price to the average value (weekday) recorded on the JEPX (Japan Electric Power Exchange) in September 2013. The spot price data are shown in Fig. 7.

3.3 Simulation method

As regard to decision making by retailers and consumers formulated as the bi-level programming problem, we conduct simulations for various proportions K_i^v of the consumer's controllable loads and the disutility $\rho_{i,t}$ of underconsumption with respect to the desired demand. Thus, we find the retailer's profit, the consumer's cost, the DN voltage ($V_{j,t}$), and the number of transformer operations at the distribution substation in 24 h (N_{Tra}). First, we quantitatively evaluate the retailer's profit and the consumer's cost and show that DR on the consumer side offer advantages for both retailers and consumers, which indicates the likely future adoption of HEMS, BEMS, and so on.

Then, based on $V_{j,t}$ and N_{Tra}, we consider the impact of DR on the distribution system voltage. With the introduction of HEMS and BEMS, consumers can flexibly control their power consumption, thus reducing the disutility $\rho_{i,t}$ of underconsumption with respect to the desired demand. We considered the disutility in three cases, depending on HEMS/BEMS penetration, namely, Case 1: low DR penetration, Case 2: medium DR penetration, and Case 3: high DR penetration. The values of $\rho_{i,t}$ for each case are shown in Figs. 8 to 10. For simplicity, we assumed that $\rho_{i,t}$ is equal for consumers of same type. The consumer's controllable loads depend on the type of electric appliances and the introduction of batteries or other storage; thus, we varied the proportion K_i^v of controllable loads in each case, from 0% to 30% in intervals of 5%, simultaneously for all consumers. These parameters cannot be estimated accurately because they depend on the future penetration of HEMS/BEMS and storage capacity, as well as on market size and patterns. Thus, we vary the parameters in order to

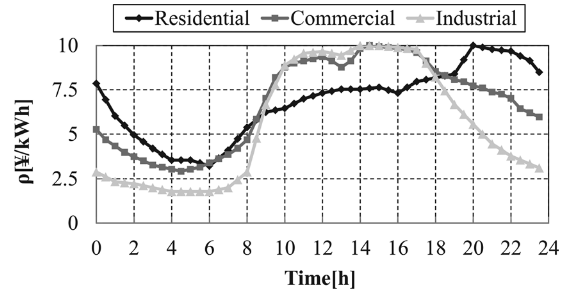

Fig. 8. $\rho_{i,t}$ in Case 1.

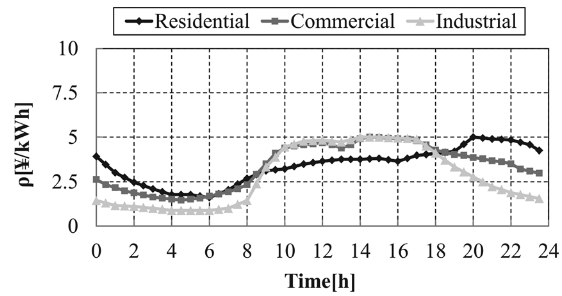

Fig. 9. $\rho_{i,t}$ in Case 2.

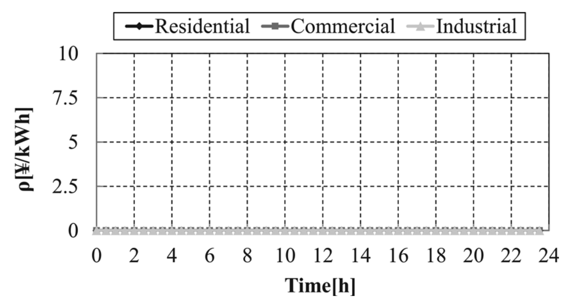

Fig. 10. $\rho_{i,t}$ in Case 3.

approximately estimate their influence on the DN voltage as liberalization progresses. Because there is a spread of the solutions (the retailer's decision variable λ_t^{sell}) obtained by PSO, we repeated the simulations 10 times under the same conditions and used the best solution (maximum retailer profit) for evaluation. In solution search by PSO, the learning coefficients used in updating the formulas for individual best solutions and swarm best solutions are set to $c_1 = 5$ and $c_2 = 0.5$, respectively. The inertial weight is $w = 0.5$ for all agents. The number of PSO agents was 50, and the number of PSO searches per simulation was 50. The simulation conditions are given in Table 1.

The flowchart of solution search for the bi-level programming problem is shown in Fig. 11. Equations (1) to (19) describe a leader–follower game in which the retailer is the leader and the consumer is the follower. Low-level problem (9) to (19) is solved by linear programming, and the resulting consumer (follower) energy consumption $P_{i,t}, t = 0, 0.5, \dots, 23.5$ is used to solve high-level problem

Table 1. Simulation parameters

Sampling time	30 (min)
Simulation period	24 (h)
K^U	1.05
K_{profit}	1.035
V_{max}	1.05 (p.u.)
V_{min}	0.95 (p.u.)
Tap width of transformer	0.0082 (p.u.)
C_{Tra}	200 (¥/times)
Exploring time of PSO	50
Number of agents of PSO	50
c_1	5.0
c_2	0.5
w	0.5

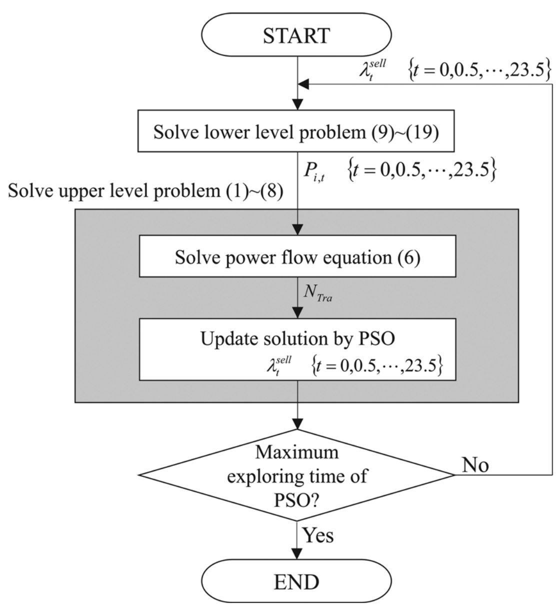

Fig. 11. Solution flowchart of bi-level programming.

(1) to (8). In the high-level problem, the number N_{Tra} of transformer operations obtained by solving power flow Eq. (6) is used in PSO to find the electricity rate λ_t^{sell}, $t = 0, 0.5, \ldots, 23.5$ so as to maximize the retailer's (leader's) profit. Low-level problem (9) to (19) is solved repeatedly based on λ_t^{sell}, $t = 0, 0.5, \ldots, 23.5$ obtained at the higher level until the number of PSO searches reaches its upper limit.

4. Simulation Results

4.1 Behaviors of retailers and consumers

In Figs. 12 and 13, the horizontal axis represents the controllable load ratio and the vertical axis represents, respectively, the retailer's profit and the total consumer cost

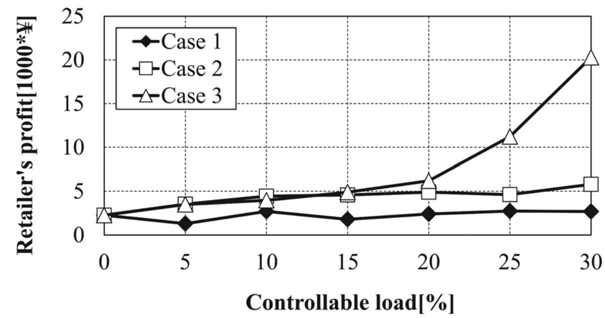

Fig. 12. Retailer's profit.

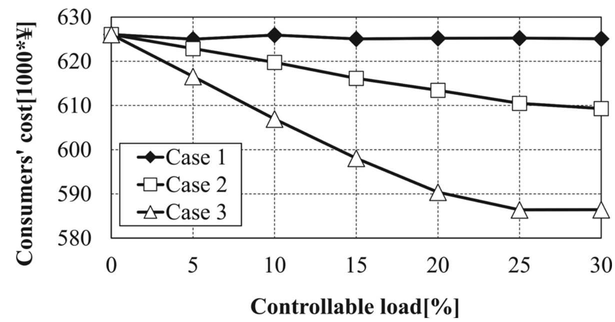

Fig. 13. Consumer's cost.

(total cost of residential, commercial, and industrial loads connected to the DN), found by solving the bi-level programming problem. The diagrams confirm the following.

(1) The retailers can gain more profit with a higher controllable load ratio Ki^v of consumers, and with a smaller disutility $\rho_{i,t}$.

(2) The consumer's cost (the sum of the power purchase cost and disutility) tends to decrease with an increasing controllable load ratio Ki^v of consumers, and with a decreasing disutility $\rho_{i,t}$.

The above results (i) and (ii) are discussed below.

4.1.1 Retailer's profit

As can be seen from Fig. 12, the retailer's profit tends to grow in every case with an increasing controllable load ratio Ki^v. In addition, in contrast to Cases 1 and 2, the retailer's profit in Case 3 increases sharply with Ki^v above 20%. We explain this fact by using the electricity rate and power consumption in Case 3 as shown in Figs. 14 to 18. Specifically, Figs. 14 and 15 pertain to the electricity rate (selling price), with the latter being a close-up view of the former. In Figs. 16 to 18, the vertical axis shows the ratio of consumed power to the customer's load capacity. In Figs. 14 and 15, T_H^{spot} and T_L^{spot} pertain to time slots with high and low spot prices, respectively. The greater the power consumption in T_L^{spot}, the cheaper the retailers can

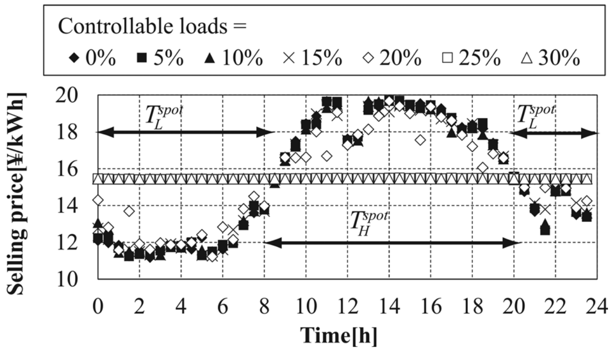

Fig. 14. Selling price in Case 3.

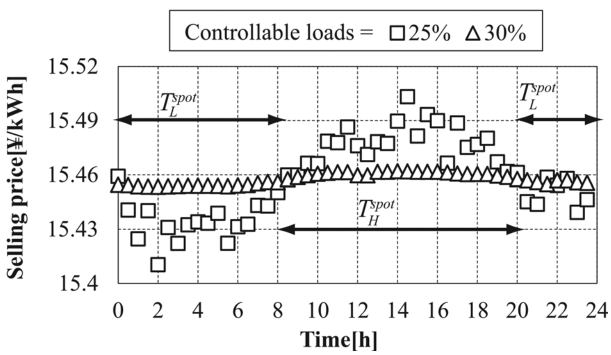

Fig. 15. Selling price in Case 3 (magnified).

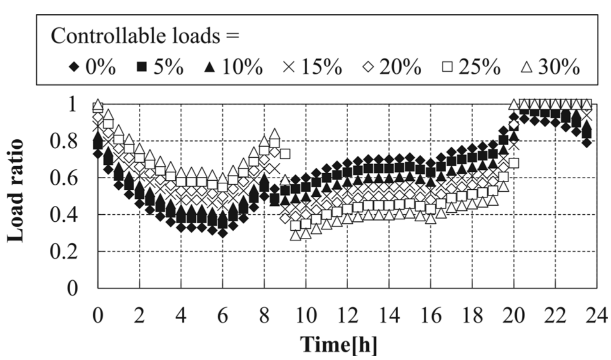

Fig. 16. Residential load in Case 3.

procure electricity from the spot market; aiming at maximum profit, the retailers set the electricity rates in T_H^{spot} higher than in T_L^{spot} so as to encourage power consumption in T_L^{spot}. As indicated by Figs. 14 to 18, the power consumption in T_L^{spot} increases with the proportion of the consumer's controllable load; thus, aiming at higher profit, the retailers increase electricity rates in T_L^{spot}. As a result, the electricity rates in T_H^{spot} decrease due to constraint (5). From Fig. 14 we may conclude that when the controllable load ratio Ki^v is small, the electricity rates grow in T_H^{spot}, and as the ratio K_{iv} increases, the electricity rates increase in T_L^{spot} and decrease in T_H^{spot}.

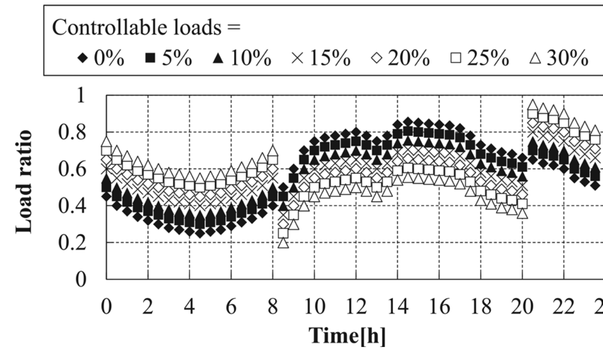

Fig. 17. Commercial load in Case 3.

When the controllable load ratio Ki^v is small, the consumer's load shift magnitude is small and the power consumption in T_H^{spot} is large; hence, the retailer's profit decreases due to a higher power procurement cost. In particular, it is difficult for consumers to shift from T_H^{spot} to T_L^{spot}, and the retailer's profit declines when the disutility $\rho_{i,t}$ and the spot price reach their peaks at about the same time, as is the case with commercial and industrial loads. The higher the ratio Ki^v, the greater the profit that the retailer can gain, and therefore, we may expect positive effects of incentives encouraging consumers to introduce HEMS, BEMS, and other DR systems.

With the parameter settings used in this study, the retailer's profit is not large, and a negative profit area exists in the vicinity of suboptimal solutions. This can be interpreted as meaning that in our model, retailers are unlikely to gain large profits, which reflects a highly competitive environment created by market deregulation.

4.1.2 Consumer's cost

Due to DR, consumers can shift loads to time slots with cheaper rates so as to buy power more cheaply. Therefore, consumers of any type can the reduce power purchase cost with a higher ratio Ki^v, of controllable loads; however, the reduction amount and rate depend on the consumer type. Let $C^N(K^v)$ denote the cost for a consumer of type N with a controllable load ratio K^v; the cost reduction rate $\eta^N(K^v)$ with reference to $K^v = 0\%$ is calculated in Eq. (20); the results are presented in Figs. 19 to 21.

$$\nu^N(K^v) = \frac{C^N(K^v) - C^N(O)}{C^N(O)}. \tag{20}$$

As can be seen from Figs. 19 to 21, the cost reduction rate due to an increase in controllable loads varies strongly with the consumer type; namely, the rate tends to be highest for industrial loads followed by commercial loads and residential loads. This can be explained as follows. When the disutility $\rho_{i,t}$ decreases or the controllable load ratio K_i^v increases, the customer can reduce the power purchase

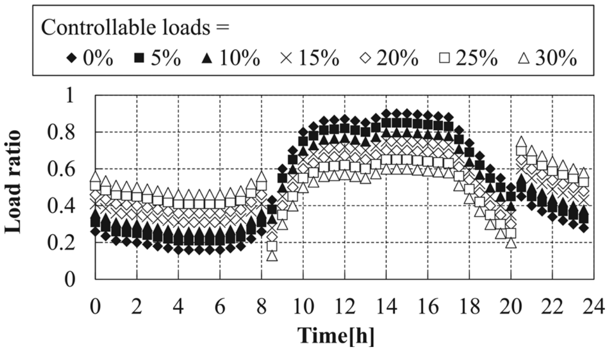

Fig. 18. Industrial load in Case 3.

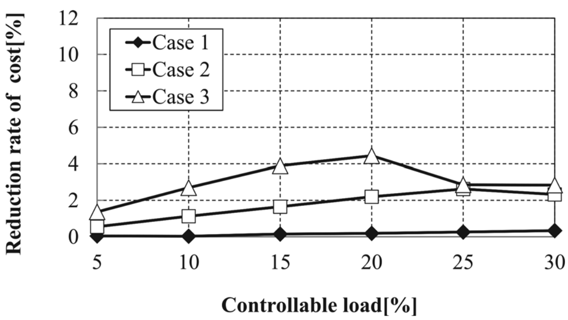

Fig. 19. η^{Nre} (residential).

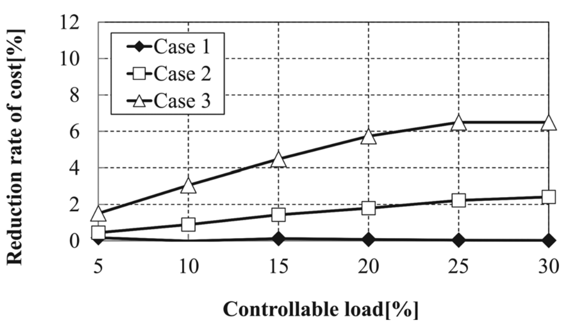

Fig. 20. η^{Nco} (commercial).

cost by shifting the load to T_L^{spot} using DR; however, the difference in the desired demand (and $\rho_{i,t}$) among customer types leads to a difference in load shifting. In addition, with residential loads having a large desired demand in the night-time hours (20 to 24 h), it is difficult to shift the T_L^{spot} load to the night hours because of load capacity constraint (12) when Ki_v exceeds 20%. Thus, consumers cannot efficiently shift loads in response to the electricity rates changed by retailers, and the cost reduction rate η^{Nre} drops. Industrial loads offer a higher cost reduction rate than commercial loads because the pre-DR power purchase cost $C^N(0)$ is much lower for industrial loads, and the cost reduction $[C^N(K^v) - C^N(0)$ is almost the same.

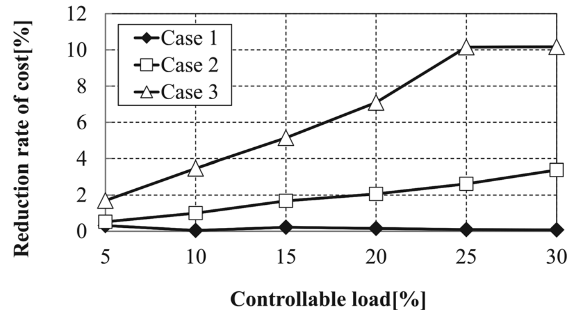

Fig. 21. η^{Nin} (industrial).

4.1.3 Behaviors of retailers and consumers

The inclination of consumers to consume energy when electricity rates are cheaper that was discovered in the numerical simulations of retailer and consumer behaviors formulated as a bi-level programming problem is also observed in existing power systems, as exemplified by electric water heaters used for load shifting to the evening hours. This can be attributed to harmony between the power companies expecting utility due to load leveling, and the consumers expecting utility due to cheaper electricity bills. In our simulations too, the retailers set the electricity rates low in T_L^{spot} when the spot price is cheap, thus encouraging consumers to shift loads to T_L^{spot} and gaining more profit. This agrees with the needs of consumers aiming at cost reduction. These results confirm that in the context of retail liberalization, the introduction of HEMS, BEMS, and so on (increase in controllable loads, reduction of disutility due to load shifts) offers advantages for both retailers and consumers; thus, the incentives created by retailers to encourage consumers to introduce HEMS and BEMS would be workable. Because retailers cannot significantly increase their profits unless HEMS and BEMS are sufficiently introduced on the consumer side, in the future one can expect the appearance of retailers seeking to obtain more profit by giving preferential treatment (better electricity rates) to consumers who install HEMS, BEMS, and other DR systems. Thus, the influence of DR in power DNs may increase with retail liberalization, and the impact of DR on voltage must be thoroughly investigated for appropriate voltage management. The voltage issues are discussed in Sections 4.2 and 4.3.

4.2 Impact on DN voltage

Here we consider the DN voltage in Cases 1 to 3, and discuss how it is affected by DR. The terminal voltage that is most susceptible to fluctuations is an important element in voltage management of a DN. The time evolution of the terminal voltage at terminal node #12 in each case is shown in Figs. 22 to 24. The symbols in the diagrams denote the

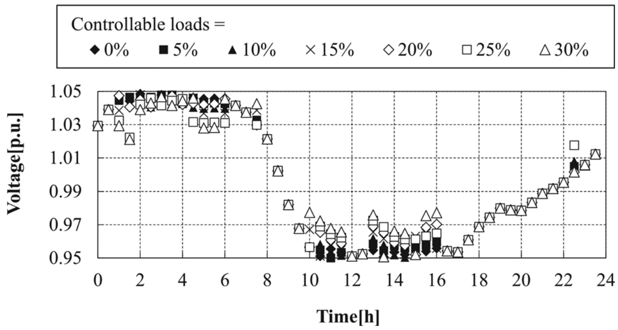

Fig. 22. Voltage at node #12 (Case 1).

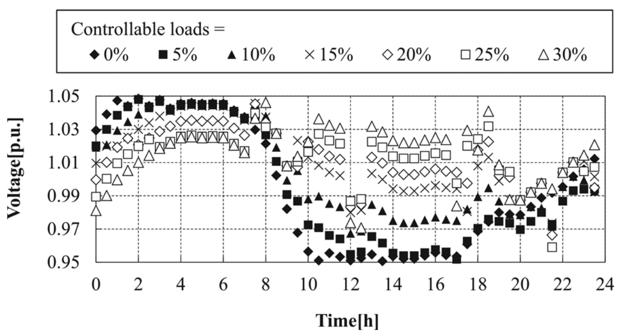

Fig. 23. Voltage at node #12 (Case 2).

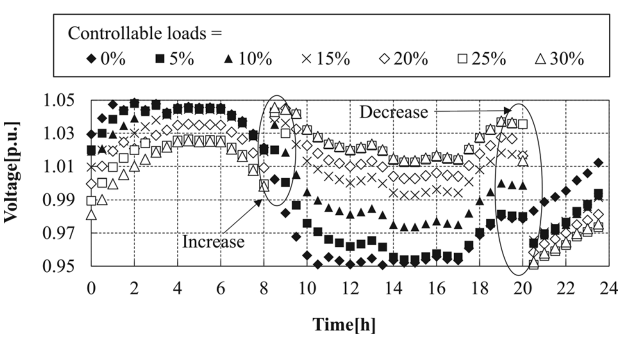

Fig. 24. Voltage at node #12 (Case 3).

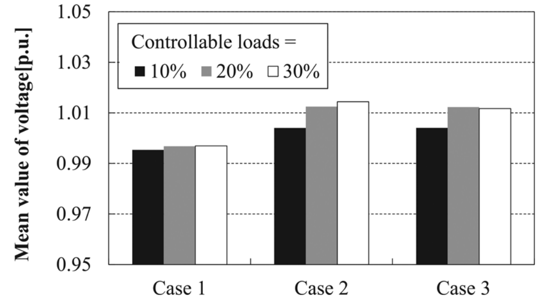

Fig. 25. Mean voltage at node #12 for 24 h.

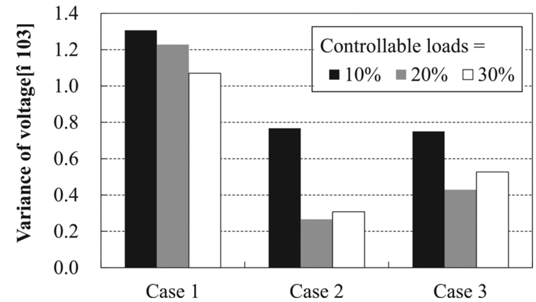

Fig. 26. Variance of voltage at node #12 for 24 h.

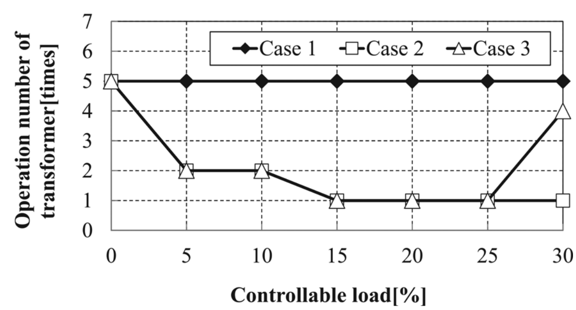

Fig. 27. Number of transformer operations.

controllable load ratio K_i^v. In addition the 24-h average voltage at node #12 is shown in Fig. 25, its variance is shown in Fig. 26, and the number of transformer operations in 24 h s shown in Fig. 27. The symbols in Figs. 25 and 26 denote the controllable load ratio K_i^v. From a comparison among Fig. 22 to 24, we can see that when K_i^v grows in Cases 2 and 3 (with a small disutility coefficient $\rho_{i,t}$), the voltage changes considerably with the introduction of DR. This is because, as shown in Figs. 16 to 18, the consumers shift more loads from the 10 to 18 h interval (the high electricity rate period) to the 20 to 8 h interval (the next morning i.e., the high electricity rate period) as the ratio of controllable loads grows. Consumers of each type shift loads from the peak period around 12 h to other time slots as the ratio of controllable loads grows, thus contributing to load leveling. As a result, the voltage is smoothed in Case 2 (Fig. 23) compared to Case 1 (Fig. 22). This is also confirmed by the fact that the voltage variance at node #12 in Case 2 is much smaller than in Case 1 (Fig. 26). Due to smaller voltage fluctuations, the distribution transformer is operated less frequently than in Case 1 (Fig. 27). On the other hand, as shown in Figs. 16 to 18, the energy consumption of all consumers changes at about 9 h and 20 h, and as a result, the voltage fluctuates strongly (Fig. 26), while the number of transformer operations in Case 3 increases when the ratio K_i^v exceeds 20% (Fig. 27). This is because when the ratio K_i^v becomes large in Case 3, with small disutility due to load shifts, consumers of all types change their loads in the vicinity of the boundary between time slots with low and high electricity rates (9 h and 20 h).

The above results confirm that the voltage in a DN tends to be smoothed when the ratio of controllable loads increases, or when the consumer's disutility due to load shift decreases. However, when the disutility is small, many consumers change their consumption at the same time, which aggravates voltage fluctuations.

4.3 Management of DN voltage with DR introduction

The better voltage smoothing in Case 2 than in Case 3 is not only due to the greater disutility $\rho_{i,t}$: another reason is that the consumer's preferences ($P_{i,t}^{Base}$, $\rho_{i,t}$) depend on the consumer type, which results in different optimal timing of load control as well as different load fluctuations. On the other hand, when many consumers in a DN have similar preferences (residential, commercial, or industrial zones), the load fluctuations occur synchronously, and large voltage fluctuations may arise even though the proportion of controllable loads is small. Especially in the case of a system like ADR, providing optimal DR automatically, consumers are assumed to constantly control their loads based on the electricity rate data so as to reduce their costs, and therefore, load control of numerous customers with similar preferences is likely to be synchronous and the trend toward strong voltage fluctuations becomes more pronounced. With sharp voltage fluctuations caused by short-term load fluctuations, the voltage may deviate from its proper range, and the voltage control devices may have to be operated more frequently to keep the voltage within its proper range, thus adding to management costs. Therefore, strategies are needed to prevent sharp load fluctuations in an entire DN, such as incentives (electricity rate discounts) to time-shift DR among consumers with similar preferences.

In the simulation results obtained in this study, consumers shift daytime loads to the night hours; thus we may assume that with retail liberalization, the consumers' DR should alleviate the problem of a leading power factor in the nighttime due to excessive installation of phase-advancing capacitors by high-voltage consumers [27]. However, the load decreases in the daytime hours, with expensive electricity, and a leading power factor occurs, which may result in voltage rises and harmonic propagation. As indicated by our simulations (Fig. 25), the network voltage increases with the ratio of controllable loads, or with decreasing disutility caused by load shifts. In addition, the load decreases in the daytime hours when consumers install photovoltaic generation systems (PV), which results in an even more strongly leading power factor in the daytime, while we may expect reverse power flow and substantial voltage rises in daytime due to PV operation. In particular, the FiT (Feed-in Tariff) scheme for renewable energy in Japan does not apply to all renewable energy generated in the residential sector but only to "excess electricity," and therefore, incentives to restrict power consumption in the daytime are attractive to residential consumers having PV, which is likely to aggravate the voltage rise. The risk of voltage rises during daytime hours is obvious. However, considering that the load patterns of each consumer type would change with retail liberalization, it may become necessary to revise the control parameters of LRTs (load ratio control transformers) and SVRs (step voltage regulators), as well as SVR installation locations, the turns ratios of pole transformers, and other elements of equipment schedules.

Thus, as judged by the current power DNs with a rapid introduction of renewable energy, a more detailed investigation into the impacts of DR and market deregulation on DNs is needed for appropriate network voltage management. The abovementioned issue of voltage rises was derived from approximate solutions to a bi-level programming problem describing a Stackelberg game involving two decision-makers, namely, retailers aiming at profit maximization and consumers aiming at cost minimization, and the behaviors of the decision-makers were predicted approximately. Therefore, for more accurate evaluation of the impacts on DNs, it is important to formulate the problem using parameters that simulate the behaviors of the decision-makers more precisely. For this purpose, one can, for example, conduct subjective tests regarding the utility/disutility to consumers involved in DR verification projects [1, 2].

5. Conclusions

As a basic study of the impacts of DR on power distribution systems under the liberalization of electricity retail, we formulated a bi-level programming problem involving two decision-makers, a retailer and consumers, and evaluated the impacts by numerical simulations. The results showed that the incentives for the introduction of DR systems such as HEMS and BEMS are workable because DR offers advantages to both retailers and consumers. We also showed that such DR systems may substantially change the network voltage, and that rational load control on the consumer side such as ADR may lead to rapid, large voltage fluctuations. In addition, numerical fluctuations using a decision-making model differentiated by consumer type suggested that the consumer type should be taken into account when creating voltage management strategies under market liberalization.

In this investigation we did not consider competition among retailers or risk hedging in forward transactions, nor fluctuations of spot prices because of bidding, transactions on the hour-ahead market, and so on. In the future, we plan to consider these factors for more accurate prediction of the behaviors of retailers and consumers under retail liberalization, and to investigate appropriate methods of voltage management, including equipment scheduling toward liberalization.

Acknowledgment

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Appendix A

Parameters of DN model

The parameters of DN model used in this study are given in Table A1. In the table, *Upper* and *Lower*

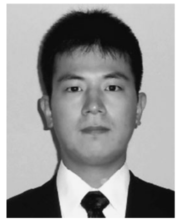
Table A1. Parameters of distribution network model

Node		Line data between two nodes			Load capacity at lower node		
Upper	Lower	R (Ω)	X (Ω)	B (μ S)	P (kW)	Q (kvar)	SC (kvar)
1	2	0.035	0.277	0.000	0	0	0
2	3	0.031	0.386	2.386	0	0	0
3	4	0.071	0.112	2.158	0	0	0
4	5	0.005	0.009	0.000	480	348	0
3	6	0.126	0.128	1.784	204	150	0
6	7	0.076	0.077	1.784	276	158.4	0
3	8	0.131	0.386	2.386	1386	792	0
8	9	0.066	0.193	2.386	0	0	0
8	10	0.075	0.077	1.767	0	0	0
10	11	0.076	0.077	1.712	612	96	360
10	12	0.203	0.078	33.709	153.6	103.2	0
8	13	0.076	0.042	36.701	204	554.4	720

Notes Three-phase 4.16 kv, 10 MVA base.

pertain to nodes on the upper-level side (substation side) and low-level side (terminal side), respectively. The line capacity is the total load capacity of consumers connected to the lower-level node; the consumer's load capacity is determined by the consumer type. In the numerical simulations, the reference capacity and reference voltage were set to 10 MVA and 4.16 kV, respectively.

AUTHORS (from left to right)

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