Negawatt planning via stochastic programming

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Abstract: Power suppliers generate electricity constantly to ensure that the power generated equals demand. The vast daily fluctuations in electricity demand result in very high generation costs. One of the solutions to this problem is known as negawatt trading. This is a contract between power suppliers and customers that involves the promise of a fixed amount of power demand reduction in advance. In this study, a stochastic programming model is formulated for a negawatt planning operation, considering the uncertainty of the power demand and the probability of the customer's failure to reduce it. The stochastic programming method was used to optimise the operation, maximising the profit for customers, and its effect was verified. The experiment results show that customers can choose an operation method tailored to their strategy while controlling the value of the failure probability. Compared to using a deterministic model, this stochastic programming model ensures high profits and a stable supply to consumers.

Keywords: electric power; negawatt trading; stochastic programming.

Reference to this paper should be made as follows: Yamada, M., Fukuba, T., Shiina, T. and Tokoro, K. (2020) 'Negawatt planning via stochastic programming', *Asian J. Management Science and Applications*, Vol. 5, No. 1, pp.40–55.

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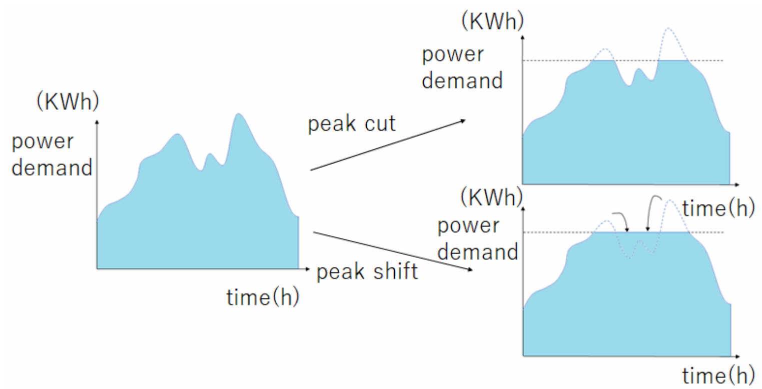
This paper is a revised and expanded version of a paper entitled 'Negawatt planning via stochastic programming' presented at 2019 Asian Conference of Management Science & Applications (ACMSA2019), Penglai, Shandong, China, 11–14 October 2019.

1 Introduction

Electrical energy is difficult to store. Although there is technology for converting and storing energy, such as storage batteries, a technology with large storage capacity has not yet been developed. Therefore, power suppliers generate electricity constantly to ensure that the power generated equals demand (Wood, 1984). The vast daily fluctuations in electricity demand require power suppliers to operate generators to maintain the balance of electricity supply and demand constantly, resulting in very high generation costs. Demand response (DR) is attracting attention as a solution to these problems. According to the Ministry of Economy, Trade and Industry of Japan (n.d.), DR means changing the consumer's power demand pattern by controlling the energy resource. The US Federal Energy Regulatory Commission (FERC), defines DR as changes in electric usage by demand-side resources from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardised. DR also includes hourly tariffs for residential, commercial, and industrial use; reduced demand during peak hours; and pricing for homes.

DR allows power suppliers to reduce their power generation cost through peak-shaving and peak-shifting of power demand (Figure 1) (Zhao et al., 2013). Simply reducing the amount of power consumption when the power is at maximum demand is called peak-shaving. Peak-shifting is the use of power that was to be used during the maximum demand period when the demand for power is low.

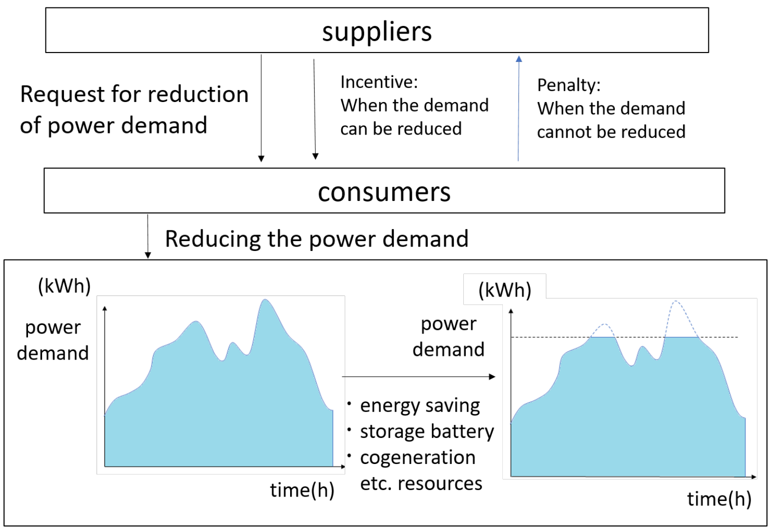
Figure 1 Peak-shaving and peak-shifting of power demand (see online version for colours)



There are two types of DR programs: time-based and incentive-based (Magnago et al., 2015). A time-based DR program promotes peak-shaving and peak-shifting by adjusting electricity rates. Examples of price-type DR policies include time-of-use rates and critical peak prices. In time-of-use rates, rates vary depending on the time, season, and type of weekday (weekday or weekend/holiday). Rates for power are higher during peak hours and lower during low demand times, where the price for each period is predetermined and constant. Time-of-use rates help control electricity demand by charging different rates for peak and off-peak periods. Increasing the power price during a peak time when the power demand is expected to be unusually high may reduce demand. Critical peak prices are electricity rates for which a higher unit price is applied depending on the specific conditions, such as an emergency or high wholesale market prices. Critical peak prices give consumers advance notice that the power price during peak hours will be higher than usual, especially when demand is likely to be high the next day, and allows them to shift their peak demand. Power suppliers make huge capital investments in equipment for these rare emergency peak hours, which may not even amount to 10 hours per year. Power suppliers can reduce this capital investment by implementing emergency peak charges.

In an incentive-based DR program, power suppliers contract with consumers to pay rewards when consumers meet their contract conditions. Examples of incentive-based DR policies include direct load control and negawatt trading. According to Alder and Fischl (1977) and Momoh (2012), direct control uses a communication system to transmit direct control of load from utility to customers. Direct load control incentivises cooperation and the electric utility controls power consumption by, for example, air conditioners, remotely during demand peaks. Lovins (1990) proposed the term negawatt to refer to power saving in terms of reducing power consumption. Negawatt trading is a contract between power suppliers and customers that treats the saved or unused power as if it were generated power. It involves the promise of a certain amount of power demand reduction in advance. For example, an electric power company requests that consumers raise the temperature of the air conditioner by 3 degrees Celsius from 12:00 to 14:00 and reduce the amount of electricity used by about 1,000 watts. The customer receives an incentive to comply with the conditions for the promised time. If the customer cannot meet the contract, then the customer pays a penalty, as Figure 2 shows. This mechanism offers two advantages: the consumer can receive an incentive by reducing demand and the electric power company can reduce its generation cost by suppressing demand during peak periods.

Figure 2 Negawatt trading (see online version for colours)



Vardakas et al. (2015) surveyed demand response programs comprehensively and classified the optimisation models into five categories:

a minimising electricity cost

b maximising social welfare

c minimising aggregate power consumption

d minimising both electricity cost and aggregate power consumption

e maximising social welfare and minimising aggregate power consumption.

Molderink et al. (2009) proposed a minimisation algorithm based on integer linear programming to control domestic electricity and heat demand, as well as the generation and storage of heat and electricity. Behrangrad et al. (2010) analysed the effect of demand response resource utilisation by using a market clearing framework based on mixed integer programming. In maximising social welfare, the objective function is the difference between the total profit of the utility and the total cost of the energy generator and transmission networks. Cecati et al. (2011) proposed an energy management system to optimise smart grid operation using mixed integer nonlinear programming. This energy management system allows the SG to participate in the open market like an aggregator of distributed energy resources. The minimisation of aggregate power consumption is typically formulated as a problem for consumers to find the optimal solution they can use to schedule their loads during off-peak hours. Kriett and Salani (2012) proposed a generic mixed integer linear programming model to minimise the operating cost of a residential microgrid. Silva et al. (2012) proposed a method for energy resource scheduling in smart grids based on genetic algorithm considering one-day, one-hour, and five-minute ahead scheduling. The minimisation of both electricity cost and aggregate power consumption is an optimisation problem that considers multiple objective functions and various optimisation schemes. Ferreira et al. (2012) used robust optimisation techniques to propose an optimisation model for consumption scheduling considering power prices. To maximise social welfare and minimise aggregate power consumption, Kallitsis et al. (2012) proposed a social welfare maximisation framework for optimal power allocation in smart power grids. Using this framework, the data network component of the smart grid is optimised and the delay in communication is reduced. Samadi et al. (2010) proposed an optimal real-time pricing algorithm in a smart grid that maximises the aggregate utility of all users and minimises the cost imposed to the energy provider.

Stochastic programming is rarely applied in research on demand response programs. In this study, we formulate a stochastic programming model for a negawatt planning operation considering the uncertainty of the power demand and the probability of the customer's failure to reduce it. We use stochastic programming to optimise the operation by maximising customers' profit and verify its effect. Otsuki (2016) developed a model using a scenario tree of power demand in consideration of the negawatt plan. This model makes decisions in multiple stages so that customers who have contracted negawatt transactions can achieve power reduction considering actual power demand fluctuations. However, Otsuki's model does not account for the probability of not being able to meet the promised reduction. This study considers the constraint of failure tolerance probability. Using stochastic programming, we optimise operations, allowing consumers to maximise their profits by trading.

2 Stochastic programming

2.1 General framework

Mathematical programming problems are used in a wide variety of fields, for example, engineering fields such as industrial production, energy, or transportation. These often involve uncertainty in objective functions and constraints. For example, in the energy field, electricity demand and power generated by wind and solar power, or renewable energy, should not be treated as deterministic values. Planning under such uncertainty involves risks. To avoid the risk arising from uncertain situations, it is necessary to model this uncertainty and to consider the stochastic fluctuation factor. Stochastic programming is an optimisation method that incorporates uncertainty factors directly into the model, as in Birge and Louveaux (1997), Kall and Wallace (1994) and Shiina (2015). Moreover, Zheng et al. (2015) review the application of stochastic programming to unit commitment. In this paper, we formulate the problem with a new framework that combines two approaches, stochastic programming with recourse and probabilistic constrained problem.

2.2 Stochastic programming with recourse

We first form the basic two-stage stochastic linear programming problem with recourse (SPR) as:

(SPR):

$$
\begin{aligned}
&\min\ c^\top x + \mathcal{Q}(x) \\
&\text{s.t.}\quad Ax = b \\
&\qquad\quad x \geq 0 \\
&\text{where}\quad \mathcal{Q}(x) = E_{\tilde{\xi}}[Q(x,\tilde{\xi})] \\
&\qquad\qquad Q(x,\xi) = \min\{q^\top y(\xi) \mid Wy(\xi) = \xi - Tx, y(\xi) \geq 0\}, \xi \in \Xi
\end{aligned}
$$

In the SPR formulation, c is a known n_1-vector, b a known m_1-vector, $q(>0)$ a known n_2-vector, and A and W are known matrices of size $m_1 \times n_1$ and $m_2 \times n_2$, respectively. The first stage decisions are represented by the n_1-vector x. We assume that the m_2-random vector $\tilde{\xi}$ is defined in a known probability space. Let Ξ be the support of $\tilde{\xi}$; that is, the smallest closed set such that $P(\Xi) = 1$.

Given a first stage decision x, the realisation of the random vector ξ of $\tilde{\xi}$ is observed. The second stage data ξ become known. Then, the second stage decision $y(\xi)$ must be taken to satisfy the constraints $Wy(\xi) = \xi - Tx$ and $y(\xi) \geq 0$. The second stage decision $y(\xi)$ is assumed to cause a penalty of q. The objective function contains a deterministic term $c^\top x$ and the expectation of the second stage objective. The symbol $E_{\tilde{\xi}}$ represents the mathematical expectation with respect to $\tilde{\xi}$, and the function $Q(x,\xi)$ is called the recourse function in state ξ. The value of the recourse function is given by solving a second stage linear programming problem.

It is assumed that the random vector $\tilde{\xi}$ has a discrete distribution with finite support $\Xi = \{\xi^1, \ldots, \xi^S\}$ with Prob$(\tilde{\xi} = \xi^s) = p^s, s = 1, \ldots, S$. A particular realisation ξ of the random vector $\tilde{\xi}$ is called a scenario. Given the finite discrete distribution, the problem, SPR, is restated as the deterministic equivalent problem (DEP)for the SPR.

(DEP):

$$
\begin{aligned}
&\min\ c^\top x + \sum_{s=1}^{S} p^s Q(x,\xi^s) \\
&\text{s.t.}\quad Ax = b \\
&\qquad\quad x \geq 0 \\
&\text{where}\quad Q(x,\xi^s) = \min\{q^\top y(\xi^s) \mid Wy(\xi^s) = \xi^s - Tx, y(\xi^s) \geq 0\}, s = 1, \ldots, S
\end{aligned}
$$

To solve the DEP, we use an L-shaped method.

2.3 Probabilistic constrained problem

We provide the following chance-constrained programming problem:

$$\min\ h(x) \tag{1}$$

$$\text{s.t.}\quad h_0(x) = P(g_1(x,\xi) \geq 0, \ldots, g_r(x,\xi) \geq 0) \geq p_0, p_0 \in [0,1] \tag{2}$$

$$
\begin{aligned}
&h_1(x) \geq p_1 \\
&\vdots \\
&h_m(x) \geq p_m
\end{aligned} \tag{3}
$$

$x \in \Re^n$ is a decision variable vector and $\xi \in \Omega \subset \Re^q$ is a random vector. We assume that $(\Omega, \mathcal{F}, P)$ is a known probability space, where a family $\mathcal{F}$ of events; that is, subsets of Ω and the probability distribution P on $\mathcal{F}$, are given. We define $h, h_0, h_1, \ldots, h_m$ and $g_1, \ldots, g_r$ on $\Re^n$,$\Re^{n+q}$ respectively. p_0 is a prescribed level of reliability. If g_i is a linear function of x and ξ; that is, $g_i(x, \xi) = T_i x - \xi_i, i = 1, \ldots, r$, then the chance-constraint (2) is indicated as follows. Here, T_i is the i^{th} row vector of the $r \times n$ matrix T.

$$
P(Tx \geq \xi) \geq p_0 \tag{4}
$$

Next, we define a joint distribution function of ξ as $F(z) = P(\xi \leq z)$, and the chance-constraint becomes:

$$
F(Tx) \geq p_0 \tag{5}
$$

3 Problem setting

The DR system was introduced in Japan in 2017. In large-scale buildings and factories, which have multiple customers, the time slots and reduction amounts that can be accommodated are different for each customer. Because negawatt trading is an important load-balancing method, a constant amount of reduction is always required.

The problem background in this study is as follows. The minimum time-slot unit is 1 hour. The time slot is referred to as a commitment slot for which the power demand reduction has already been determined under the contract. The customer reduces the power demand below the baseline B by using their own resources; for example, storage batteries, energy saving, or cogeneration, during the commitment slot. If customers meet the contract conditions for the commitment slot, they receive an incentive. On the contrary, if they cannot meet the contracted conditions at the promised time, they pay a penalty to the supplier.

In this study, the problem is formulated as a stochastic programming model.

3.1 Notations

Sets

T_c The set of commitment slots.

K The set of resources that can reduce demand.

S The set of scenarios in demand fluctuation.

Variables

w_{tk} Amount reduced by resource k at time t.

y_{tk} 0-1 decision variables, 1 if the customer reduces demand for resource k at time t, 0 otherwise.

z_t^s 0-1 decision variables, 1 if the demand reduction is not successful at time t, under scenarios, 0 otherwise.

Parameters

D_t^s Actual demand at time t under scenario s.

p^s Occurrence probability of scenario s.

A_{tk} Upper limit of the demand on resource k that can be reduced at time t.

C_{tk} Reduction cost of resource k at time t.

M_k Limit of total reduction hours for resource k.

N_k Limit of total reduction amount for resource k.

D_{0t} Expected demand at time t.

B Demand baseline.

Q Incentive paid per KWh of electricity demand reduction.

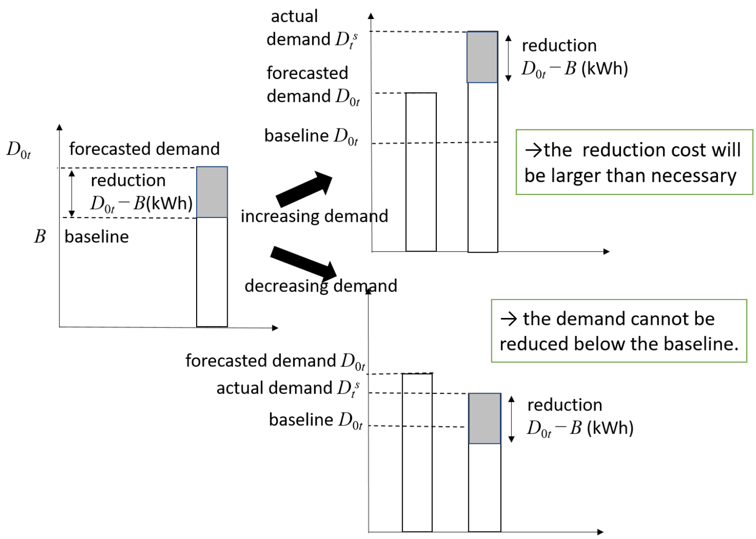
R_t The penalty imposed if the reduction fails at time t.

α Probability of failure to reduce demand at each time.

D_{0t} is the expected demand, and D_t^s is the value of the demand under scenarios considering fluctuation. Actual demand fluctuates because of weather and other factors. We consider making a plan for reduction with forecast demand and reducing it. The target demand reduction at time t is $D_{0t} - B$. If the actual demand D_t^s is greater than the forecast value D_{0t}, then the demand cannot be reduced below the baseline B, and the contract cannot be satisfied. If the actual demand D_t^s is less than the forecast value D_{0t}, then the contract can be satisfied, but the reduction cost will be larger than necessary, as Figure 3 shows. To account for these fluctuations, we represent the random demand using a scenario tree. We generate the scenario from equation (14). Figure 4 provides an example scenario tree.

We define the total demand for electricity during period t as a random variable $\tilde{D}_t$. We assume that $\tilde{D}_t$ is defined on a known probability space and has a finite discrete distribution. Let D_t be a realisation of random variable $\tilde{D}_t$. A sequence of the realisation of electricity demand $D = (D_1, ..., D_T)$ is called a scenario. We assume that we have a set of S scenarios, $D^s, s = 1, ..., S$. We associate a probability p_s with each scenario $D^s, s = 1, ..., S$, and describe the scenario using a scenario tree.

Figure 3 Demand fluctuations (see online version for colours)



3.2 Formulation

We formulate the problem using stochastic programming with recourse, including chance constraints.

$$\max \sum_{s\in S} P^s \sum_{t\in T_c} \{(D_{0t}-B)\cdot Q_t\cdot(1-z_t^s) - \sum_{k\in K} C_{tk}w_{tk} - R_t z_t^s\} \tag{6}$$

s.t.

$$\sum_{k\in K} w_{tk} \geq (D_t^s - B)(1-z_t^s) \qquad \forall t\in T_c, \forall s\in S \tag{7}$$

$$0 \leq w_{tk} \leq A_{tk}y_{tk} \qquad \forall t\in T_c, \forall k\in K \tag{8}$$

$$\sum_{t\in Tc} y_{tk} \leq M_k \qquad \forall k\in K \tag{9}$$

$$\sum_{t\in Tc} w_{tk} \leq N_k \qquad \forall k\in K \tag{10}$$

$$\sum_{s\in S} \frac{z_t^s}{|S|} \leq \alpha \qquad \forall t\in T_c \tag{11}$$

$$y_{tk}\in\{0,1\},\ w_{tk}\in R \qquad \forall t\in T_c, \forall k\in K \tag{12}$$

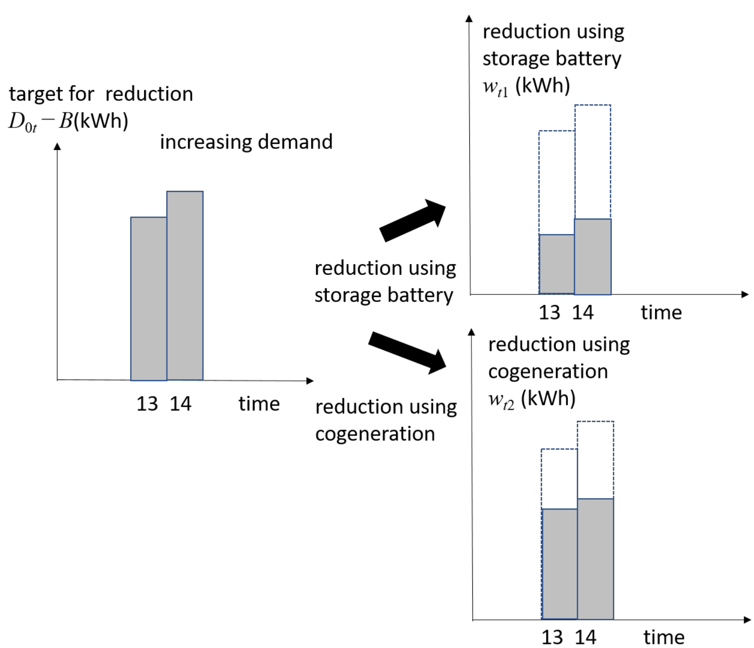
$$z_t^s\in\{0,1\} \qquad \forall t\in T_c, \forall s\in S \tag{13}$$

Considering demand fluctuation, we express the set of scenarios as $S = 1, 2, ..., |S|$. We formulate the negawatt planning problem by maximising the expected profit value. Objective function (6) maximises the expected value of the customer's total profit.

The first term represents the customer's expected reward when he or she meets the contract conditions for the promised time. The second and third terms represent the cost of the power demand reduction and the customer's expected penalty if he or she cannot meet the contract conditions at the promised time, respectively. Constraint (7) represents the relationship between the total reduction amount and z_t^s. If the demand reduction is successful at time t under scenario s, then $z_t^s = 0$, otherwise $z_t^s = 1$. Constraint (8) represents the restrictions on the hourly reduction capacity of each resource. Constraint (9) represents the restriction on the total reduction hours of each resource. Constraint (10) represents the constraint on the total reduction capacity of each resource. Constraint (11) represents the constraint of the reduction failure rate at each time slot. This formulation is based on stochastic programming with recourse because it accounts for the expected value of profit for each scenario. In addition, since this formulation includes probabilistic constraint (11), it can be regarded as a framework having both features.

Here, the supplier sets the target for reduction in the peak time from 13:00 to 15:00, as in Figure 4. Customers make reductions using multiple power reduction options. For example, energy can be stored in a storage battery in advance and used during peak hours, they can reduce power through cogeneration to generate power. Since it takes fluctuations in power demand into account, it may or may not respond to demand reduction.

Figure 4 Demand reductions using resources (see online version for colours)



3.3 Comparison of optimisation models

We evaluate the effectiveness of the proposed model using the value of the solution of the stochastic programming problem (VSS) (Birge and Louveaux, 1997). VSS is defined as VSS = EEV – RP. EEV represents the expected cost of using a solution of the deterministic problem, where we replace the value of a random variable by its expected value or set it to a specific scenario value. RP is the optimal objective function value of the stochastic programming problem. Theoretically, the relationships RP $\leq$ EEV and VSS ≥ 0 hold.

4 Numerical experiments

4.1 Scenario generation

The demand in each scenario is set under the following conditions.

- all scenarios are generated based on normal distribution
- the demand fluctuation is set to increase as time progresses from the initial time $t = 0$
- all scenarios have an equal probability of occurrence.

The demand under each scenario is generated by the following formula to satisfy the above three conditions.

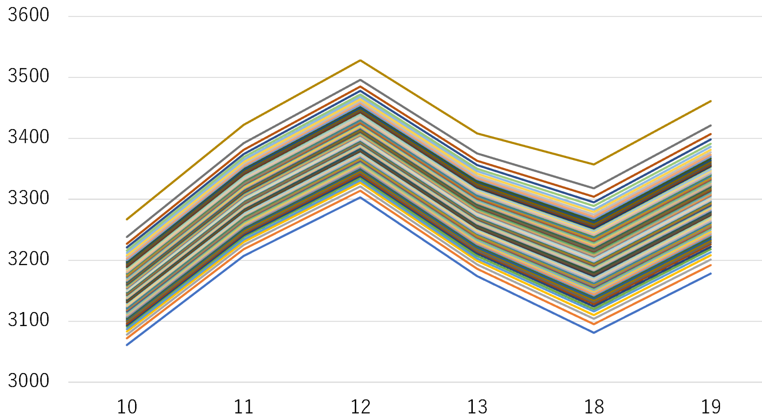
$$D_t^s = D_{0t} + \sqrt{t - t_0} \times \sigma \times F^{-1}(s/|S|) \tag{14}$$

The function F is the cumulative distribution function of the standard normal distribution. Expected demand at time t is shown in Table 1 based on Tseng (2001). We illustrate the scenarios using the scenario tree in Figure 5.

Table 1 The value of D_{0t}

t	D_{0t} *(kWh)*	t	D_{0t} *(kWh)*
1	1,025	13	3,275
2	1,000	14	2,950
3	900	15	2,700
4	850	16	2,550
5	1,025	17	2,725
6	1,400	18	3,200
7	1,970	19	3,300
8	2,400	20	2,900
9	2,850	21	2,125
10	3,150	22	1,650
11	3,300	23	1,300
12	3,400	24	1,150

Figure 5 Actual demand value D_t^s at each commitment slot t under scenario s (see online version for colours)



4.2 Resource attributes

In this study, a large-scale building is defined as a consumer with storage batteries, co-generation, and nine tenants. Each of these nine tenants can save energy. The characteristics of each resource are generated from uniform distribution as shown in Table 2.

Table 2 Attributes of each reduced resource

k	*1*	*2*	*3*
Resource	*Storage battery*	*Cogeneration*	*Energy saving*
A_{tk} (kWh)	100∼250	100∼400	5∼30
C_{tk} (yen)	10∼30	10∼30	60∼100
M_k (hours)	24	24	1∼3
N_k (kWh)	100∼250	–	–

In addition, the upper limit of reduction of energy saving at time t $(= A_{tk})$ is as follows: If the limit of total reduction hours is $M_k = 1, 2, 3$, then saved energy A_{tk} is 20∼30, 10∼20, and 5∼10, respectively.

4.3 Other parameters

We set the other parameters under the following conditions:

- The demand baseline $(= B)$ is 3,000 (kWh).
- The commitment slot is the period when D_{0t} is greater than or equal to 3,000 (kWh); that is, 6 hours from 10:00, 11:00, 12:00, 13:00, 18:00, and 19:00. We generate the actual demand value at each commitment slot t under scenario s as in Figure 5.

- The number of scenarios ($= |S|$) is set to 100.
- The incentive amount paid per kWh of electricity demand reduction ($= Q$) is 100 yen.
- A penalty ($=R_t$) double the incentive amount at time slot t is imposed for failure to reduce electricity demand at time t.
- Since the amount of incentive Q paid per kWh of power demand reduction is 100 yen, the amount of incentive at time t is $(D_{0t} - B)Q$.
- The penalty R_t at time t is twice the total incentive paid for each successful reduction at time t.

Table 3 Incentive and penalty values for each commitment slot

t	D_{0t} *(kWh)*	*Incentive* $(D_{0t} - B)Q$ *(yen)*	*Penalty* R_t *(yen)*
10	3,150	15,000	30,000
11	3,300	30,000	60,000
12	3,400	40,000	80,000
13	3,275	27,500	55,000
18	3,200	20,000	40,000
19	3,300	30,000	60,000

4.4 Experiment results and considerations

We perform two experiments to evaluate the model. In the first experiment, we solve the problem while varying the upper limit value α. We change the value of α to see the outcomes for the reward, reduction cost, penalty, and total profit of the customer. The second experiment shows the effectiveness of the stochastic programming model. In the stochastic programming model, we optimised the operation based on a set of scenarios. Otherwise, the deterministic model assumes only one scenario.

Figure 6 shows the reduction cost, penalty, and reward value for the numerical experiment while changing the value of α. Figure 7 shows the transition of the total profit of the customer. These results show that the expected value of the customer's total profit increases according to α. The optimal solution when the value of α is small is a feasible solution when α is large. We can conclude that as α increases, the feasible region expands. Therefore, when α is large, the number of scenarios in which reduction fails when the incentive or penalty is small increases.

The negawatt plan involves high risk when α is large because the consumer can allow a reduction failure by increasing the value of α. Therefore, the customer chooses an operation method such as increasing the gross profit, or the stable operation method, in which the reduction failure probability is limited by controlling the failure probability value.

Figure 6 Reduction cost, incentive, and penalty value (see online version for colours)

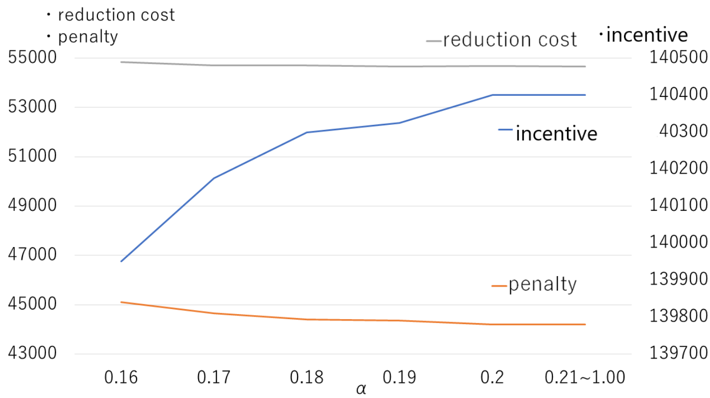


Figure 7 Customer's total profit (see online version for colours)

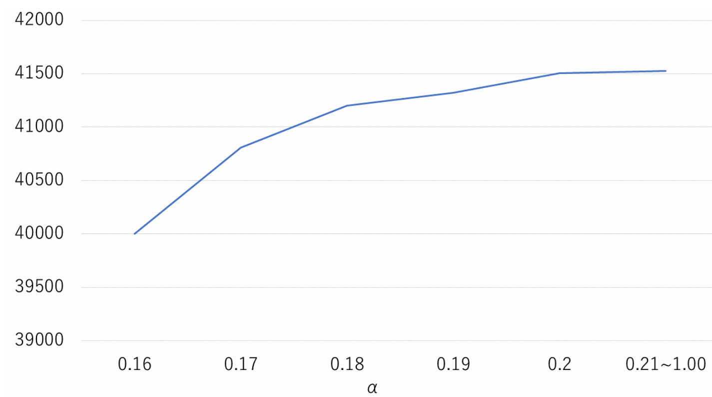


Figure 8 Total profit for the proposed method and the deterministic model (see online version for colours)

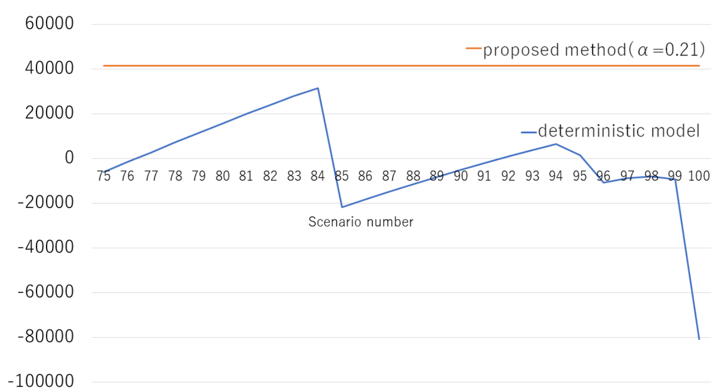


Figure 8 and Table 4 show the results of the reduction based on the plan under the proposed method and the plan that assumes only one scenario. In the deterministic model, we calculate the expected profit by applying the solution obtained assuming only one fixed scenario to all the scenarios. Table 4 show the plan with the highest value for comparison to the deterministic method. Compared to the result of the deterministic model, the proposed method enables high profits and stable supply.

Table 4 Comparison of results for each model

Model	*Proposed method (α = 0.21)*	*Deterministic model*
Incentive	140,400	136,500
Penalty	44,200	52,000
Reduction cost	54,673	53,057
Total profit	41,527	31,443

The results show that stochastic programming is beneficial for both customers and suppliers. Customers can choose a profitable operation plan by setting the failure tolerance probability. It is also effective for suppliers because they can achieve a stable supply with the smallest penalty when many customers engage in negawatt trading.

5 Conclusions

In this study, we created a stochastic programming model that allows customers to maximise profits with a negawatt plan while accounting for the upper limit of the failure probability of reduction. We show that the consumer's expected value of profits increases by setting the allowable failure probability to a large value. Compared to the results of the stochastic programming method and the negawatt plan without considering the fluctuation of demand, the stochastic programming method yielded a higher total profit and a lower penalty. From this fact, we can conclude that by using stochastic programming, negawatt planning is profitable for the consumer and a stable supply is possible for the supplier.

References

Alder, R.B. and Fischl, R. (1977) 'Security consideration economic dispatch with participation factors', *IEEE Transactions on Power Apparatus and Systems*, Vol. 96, No. 2, pp.347–356.

Behrangrad, M., Sugihara, H. and Funaki, T. (2010) 'Analyzing the system effects of optimal demand response utilization for reserve procurement and peak clipping', *IEEE PES General Meeting*, pp.1–7.

Birge, J.R. and Louveaux, F. (1997) *Introduction to Stochastic Programming*, Springer-Verlag, New York.

Cecati, C., Citro, C. and Siano, P. (2011) 'Combined operations of renewable energy systems and responsive demand in a smart grid', *IEEE Transactions on Sustainable Energy*, Vol. 2, No. 4, pp.468–476.

Ferreira, R.S., Barroso, L.A. and Carvalho, M.M. (2012) 'Demand response models with correlated price data: a robust optimization approach', *Appied Energy*, Vol. 96, pp.133–149.

Kall, P. and Wallace, S.W. (1994) *Stochastic Programming*, John Wiley and Sons, New York.

Kallitsis, M.G., Michailidis, G. and Devetsikiotis, M. (2012) 'Optimal power allocation under communication network externalities', *IEEE Transactions on Smart Grid*, Vol. 3, No. 1, pp.162–173.

Kriett, P.O. and Salani, M. (2012) 'Optimal control of a residential microgrid', *Energy*, Vol. 82, No. 1, pp.321–330.

Lovins, A.B. (1990) 'The negawatt revolution', *The Conference Board Magazine*, Vol. 27, No. 9, pp.18–23.

Magnago, F.H., Alemany, J. and Lin, J. (2015) 'Impact of demand response resources on unit commitment and dispatch in a day-ahead electricity market', *Electrical Power and Energy Systems*, Vol. 68, pp.142–149.

The Ministry of Economy, Trade and Industry (n.d.) *About Virtual Power Plant (VPP) and Demand Response (DR)*, in Japanese [online] https://www.enecho.meti.go.jp/category/savingandnew/advancedsystems/vppdr/about.html.

Molderink, A., Bakker, V., Bosman, M.G.C., Hurink, J.L. and Smit, G.J.M. (2009) 'Domestic energy management methodology for optimizing efficiency in Smart Grids', *IEEE Bucharest Power Tech Conference*, pp.1–7.

Momoh, J. (2012) *Smart Grid: Fundamentals of Design and Analysis*, Wiley, New York.

Otsuki, T. (2016) 'Demand response optimization based on building's characterstics', in Fujisawa, K. et al. (Eds.): *Optimization in the Real World*, *Mathematics for Industry*, Vol. 13, pp.177–194, Springer, New York.

Samadi, P., Mohsenian-Rad, A., Schober, R., Wong, V. and Jatskevich, J. (2010) 'Optimal real-time pricing algorithm based on utility maximization for smart grid', *Proc. IEEE SmartGridComm*, pp.415–420.

Shiina, T. (2015) *Stochastic Programming*, in Japanese, Asakura Syoten, Tokyo.

Silva, M., Morais, H. and Vale, Z. (2012) 'An integrated approach for distributed energy resource short-term scheduling in smart grids considering realistic power system simulation', *Energy Conversion and Management*, Vol. 64, pp.273–288.

Tseng, C. (2001) 'A stochastic model for a price-based unit commitment problem and its application to short-term generation asset valuation', in Hobbs, B.F. et al.(Eds.): *The Next Generation of Electric Power Unit Commitment Models*, pp.124–145, Springer, New York.

Vardakas, J.S., Zorba, N. and Verikoukis, V. (2015) 'A survey on demand response programs in smart grids: pricing methods and optimization algorithms', *IEEE Communications Surveys & Tutorials*, Vol. 17, No. 1, pp.152–178.

Wood, A.J. (1984) *Power Generation Operation and Control*, John Wiley and Sons, New York.

Zhao, C., Wang, J., Watson, J. and Guan, Y. (2013) 'Multi-stage robust unit commitment considering wind and demand response uncertainties', *IEEE Transactions on Power Systems*, Vol. 28, No. 3, pp.2708–2714.

Zheng, Q.P., Wang, J. and Liu, A.L. (2015) 'Stochastic optimization for unit commitment – a review', *IEEE Transactions on Power Systems*, Vol. 30, No. 4, pp.1913–1923.