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Demand-Side Management Program Planning Using Stochastic Load Forecasting with Extreme Value Theory

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Abstract – Demand-side management (DSM) is easy to apply to reduce system peak load by a utility and it can be a convenient way to control and change amount of electric usage by end-use customers. Planning and operating techniques for a DSM program are required to efficiently manage and operate the program. This paper is focused on planning technique for an incentive-based DSM program. This paper describes a stochastic model that can estimate the operating days, hours, and total capacity for efficiently planning a DSM program. A temperature stochastic process, from weather derivatives, is used in the proposed method. Temperature sensitivity is proposed to improve load forecasting accuracy. The generalized extreme value distribution is also proposed for estimating stochastic results. The results of case studies are presented to show the effectiveness of the proposed method.

Keywords: Demand-side management program, Load forecasting, Temperature stochastic process, Generalized extreme value distribution

1. Introduction

Recently, interest in demand-side management (DSM) has increased to reduce the risk of electrical energy crises from many reasons, such as extreme weather events, plant outages, transmission line failures, and fuel price spikes under a competitive electricity market environment. The goal of DSM is to change consumer electric demand to reduce peak electricity demand. Generally, DSM leads to a modification of electric demand patterns, using financial incentives, electricity tariffs, and education [1,2].

Traditionally, DSM has been viewed as a means of reducing peak electricity demand so that utilities can delay the building of power system infrastructure. There are various beneficial effects of DSM including reducing the number of blackouts and increasing the reliability of power systems. Possible benefits may also include a reduction in dependency on expensive fuel imports, reduced energy prices, and lower levels of harmful emissions to the environment. Thus, the application of DSM to power systems provides significant economic, reliability and environmental benefits [3,4].

There are various types of DSM, such as incentive- and time-based programs. Due to the rapid growth in electrical energy consumption and slow deployment of smart grid technologies, incentive-based programs are more actively used than time-based programs.

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Incentive-based DSM programs are based on the customer response to incentives paid by the electricity utility at times of high electricity prices. The aim of these incentives is to motivate customers to reduce their electrical energy consumption [5]. Incentive-based DSM programs are more widely used because they offer a convenient way to control and change the amount of electricity consumed by end-users. For example, if an electricity company informs those customers who have joined an incentive-based DSM program of the time and volume of load curtailment, they may alter their electrical energy consumption according to a prior agreement.

Planning and operating techniques are needed to efficiently manage and operate a DSM program. A planning technique for an incentive-based DSM program should contain an electric load forecasting method, because this is the most important factor in determining when and by how much demand must be reduced (e.g., operating days, hours, and total capacity). These estimated values form the basis of contracts with those customers who wish to participate in the incentive-based DSM program. An operating technique, in contrast, seeks to determine when and how to use limited DSM resources. However, systematic studies on both topics are lacking in the literature.

This paper is only focused on planning technique for the incentive-based DSM program. This paper proposes a mathematical method that can estimate operating days, hours, and total capacity of a DSM program for efficiently planning the program. To determine the details of a DSM program, week- or month-ahead load forecasting for the planned DSM program duration is positively necessary. Also, temperature forecasts are required to accurately predict short-term electrical demand because the temperature factor has the greatest impact on electrical demand over a relatively short forecast period. However, accurate temperature prediction for a future period of time is extremely difficult.

To overcome this, a probabilistic method is widely used in the existing literature. In this paper, a stochastic temperature modeling technique, a stochastic process describing the temperature change from weather derivatives, is used. A future temperature path for the planned DSM program duration can be generated using the temperature stochastic process technique [6-8].

In the proposed method, also, the generalized extreme value (GEV) distribution from extreme value theory is adopted for estimating probability results from a Monte-Carlo simulation. This model is widely used in risk management, finance, economics, and many other industries dealing with extreme or rare events [9-11].

The remainder of this paper is organized as follows. In Section 2, technical issues related to the design of a demand-side management program are discussed. In Section 3, the planning method using stochastic load forecasting with extreme value theory is explained for an incentive-based demand-side management program. Finally, the test results are presented to show the effectiveness of the proposed method in Section 4

2. Problem Description

DSM is one of the key elements to satisfy the increasing demand for electricity without additional power generation. DSM programs are used most often because the utility can conveniently control and change the amount of electric usage by the end-use customer. However, there is a lack of research on how to run a DSM program systematically. This paper proposes a mathematical method that can estimate the operating days, hours, and total capacity of a DSM program.

To operate a DSM program efficiently, the utility requires a planning technique that determines DSM operating days, hours, and total capacity. These elements are closely related with future electricity demand and the specified target level, which represents the execution point for the DSM program, set by the utility. Load forecasting for the next few weeks or months is necessary to design the details of the DSM program because the program should be planned a few weeks or months before DSM program execution. It is very difficult because of the uncertain factors, such as weather conditions. To overcome these phenomena, the temperature stochastic process and a Monte-Carlo simulation technique, which is widely used to assess the uncertainty of a random variable or a random process in economics and statistics, are used in this paper. Also, the generalized extreme value distribution is adopted for estimating probability results from the Monte-Carlo simulation.

Temperature has the largest effect on the electricity demand without social events such as day type and a holiday. Thus, if future temperature can be predicted accurately, the short-term load forecasting accuracy can be improved. However, it is impossible to accurately predict the future temperature of a few weeks or months later. To solve this, a probabilistic approach is proposed.

In this paper, a temperature stochastic process is applied to generating the future temperature path. This model is widely used to assess weather derivatives. For example, HDD (heating degree days) and CDD (cooling degree days), which are used to assess weather derivatives, can be calculated using a temperature stochastic process [8, 12].

Fig. 1 shows the maximum temperatures at Seoul for 21 consecutive years. There is strong seasonal variation and a long-term trend in the temperature. The dotted line represents a long-term trend of maximum temperatures. The slope of this line is the change rate of the long-term average temperature. Thus, the temperature modeling has to consider these characteristics. In this study, the future temperature path for the planned DSM program duration is created using a stochastic temperature model based on the stochastic differential equation. The temperature stochastic process is introduced in detail in Section 3.

The short-term load forecasting based on the future temperature path uses a base peak load and a base temperature, which are defined as the base values for the peak load forecasting of each day, as applied in the DSM program. The short-term load forecasting can be divided into daily peak load forecasting and 24 hourly load forecasting in the proposed method. Each daily peak load is forecast by the sum of the base peak load and the temperature compensation value that can be obtained from the temperature sensitivity analysis and the difference between the base temperature and each temperature value of the future temperature path. The base peak load is estimated using time series and the target level. Then, 24 hourly load forecasting for each day of the planned DSM program duration can be obtained by multiplying the daily peak load and a 24 hourly load pattern.

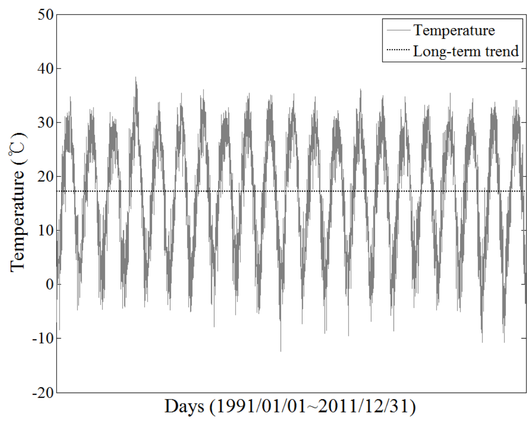

Fig. 1. Daily maximum temperatures in Seoul during 1991-2011

The DSM operating days, hours, and total capacity can be estimated by calculating the difference between the load forecasting result and the target level, which is determined by the utility. To estimate the probabilistic results, the proposed method used the generalized extreme value distribution, which is widely used to assess extreme or rare events. The coefficients of the GEV distribution function can be estimated using the results of the Monte-Carlo simulation. The procedures for the load forecasting and the probabilistic estimation of DSM program in the proposed method are described in detail in Section 3.

3. Planning Method for Incentive-based Demand-Side Management Program Using Stochastic Load Forecasting with Extreme Value Theory

This section describes a method to estimate the DSM operating days, hours, and total capacity using stochastic load forecasting with extreme value theory. There are three stages in the proposed method: data acquisition, stochastic load forecasting, and probability estimation for the incentive-based DSM program. A block diagram of the proposed method is shown in Fig. 2.

3.1 Historical data acquisition

The first stage in load forecasting with stochastic simulation is to determine user-defined data and collect historical data so that the DSM program can be planned.

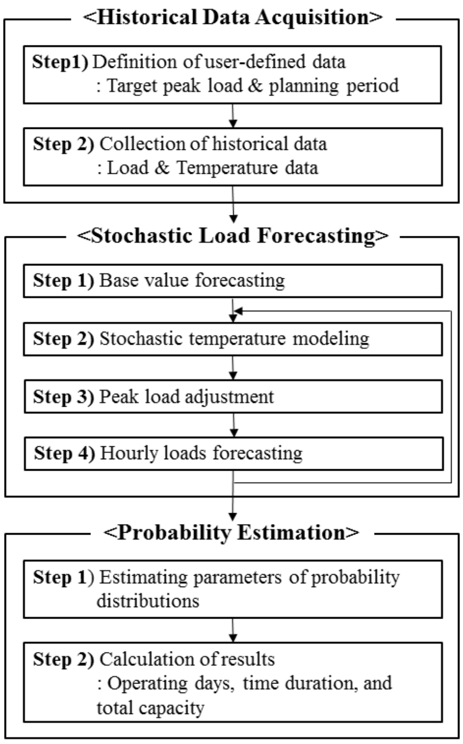

Fig. 2. Block diagram of the proposed method for the DSM program

To make a detailed DSM program plan, the target peak load and the planning period of the DSM program should first be defined. The target peak load, in megawatts, represents an operating point of the DSM program. The system operator can set this level by considering future peak load and installed generation capacity. For example, the target peak load could be designated as the system peak load of the same period in the previous year. The planning period is defined as the period of time that the DSM program is expected to be executed, such as periods of high system load.

Historical data are collected from some period of the past 20 years based on user-preference criteria. Historical data contain information about the hourly load, daily maximum temperature, and daily minimum temperature.

3.2 Load forecasting with temperature stochastic process

Load forecasting is necessary to estimate the operating days, hours, and total capacity of the DSM program. In this stage, stochastic load forecasting is described.

3.2.1 Base value forecasting

Base value forecasting is defined as the prediction of a base peak load and base temperature for daily peak load forecasting in the planning period of the DSM program. In the proposed method, the daily peak load is predicted from the base peak load and a temperature adjustment. An autoregressive moving average (ARMA) model is used to predict the base peak load of the planning period. Data used for base peak load prediction are the average values of the peak load in the same period each year, as taken from selected historical data. The base peak load is predicted using the following equation:

$$\hat{L}_t = c + \varepsilon_t + \sum_{i}^{p} \beta_i \bar{L}_{t-i} + \sum_{i}^{q} \theta_i \varepsilon_{t-i}, \quad \bar{L}_{t-1} = \frac{1}{H_{t-1}} \sum_{j} L_{t-1,j} \qquad (1)$$

where $\hat{L}_t$ is the predicted base peak load in the t year; c and ε_t are a constant and the zero mean error term in the t year; β_i and θ_i are autoregressive and moving-average parameters; p and q are the autoregressive and moving-average degree; $\bar{L}_{t-1}$ and $L_{t-1,j}$ are the average value of the peak load in the same period and the $j-th$ daily peak load in year $t-1$, which is higher than the target peak load at previous year; and H_{t-1} is the number of historical data selected from year y.

In this study, the base temperature is used to compensate the daily peak load according to the temperature sensitivity. This is calculated as the average of the temperature data from selected days that have higher daily peak loads than the target peak load in the previous year. The base temperature is defined as follows:

$$T_{base} = \frac{1}{n}\sum_{d} T_{t,d} \tag{2}$$

where T_{base} and $T_{t,d}$ are the calculated base temperature and the selected temperature on the $d-th$ day in the t year, and n is the total number of selected historical data.

Using correlation analysis between electricity and weather factors, the winter season incentive-based DSM program uses the daily minimum temperature, whereas the daily maximum temperature is used in the summer season in the proposed method.

3.2.2 Stochastic temperature modeling

A stochastic process is used to generate temperature paths for the planning period of the incentive-based DSM program. Fig. 1 shows the daily maximum temperature in Seoul for 21 consecutive years. There is strong seasonal variation in the temperature.

The temperature also shows a long-term trend. The mean temperature has actually increased each year during the last several decades. There are many reasons for this, such as global warming and the urban heating effect [6].

Thus, in a realistic model, the temperature process should reflect the periodic fluctuations and the long-term trend. Most daily temperature models in the literature capture these characteristics [7], [8]. The stochastic differential temperature model used in this paper is given by the following equation:

$$dT_t = \left\{ \frac{dT_t^m}{dt} + a\left(T_t^m - T_t \right) \right\} dt + \sigma_t dW_t . \tag{3}$$

where T_t and dT_t are the temperature process and the temperature variability at time *t*, a is the speed of the mean-reversion which can be estimated by linear regression, T_t^m is the mean reversion level at time *t*, and σ_t and dW_t are the volatility of the process and a Wiener process at time *t*.

3.2.3 Peak load adjustment

Temperature sensitivity is used for weather adjustment in daily peak load forecasting. The proposed method uses a regression-based sensitivity analysis to estimate temperature sensitivity. The following regression model attempts to relate a change in temperature to a change in the normalized peak load during the DSM program period in year t:

$$\begin{aligned} \Delta P_{t,z}^{Norm} &= s_0 + s_1 \Delta T_{t,z} + \varepsilon_{t,z} \\ \Delta P_{t,z}^{Norm} &= \frac{P_{t,z} - P_{t,x-1}}{P_{t,z-1}} \\ \Delta T_{t,z} &= T_{t,z} - T_{t,z-1} \end{aligned} \tag{4}$$

where $\Delta P_{t,z}^{Norm}$ is the $z-th$ normalized difference between the peak load and the peak load of the previous day in year *t*, $\Delta T_{t,z}$ is the $z-th$ difference between the temperature and the temperature of the previous day in year *t*, s_0 and s_1 are the constant term of the regression model and the temperature sensitivity coefficient of the normalized peak load to the temperature, respectively, and $\varepsilon_{t,z}$ is the zero mean error term.

The temperature coefficient can be estimated by OLS regression using the normalized peak load and the temperature data from the planning period in the previous year. The temperature coefficient can be obtained by minimizing the following sum of squares of the residual:

$$\sum_{z} \left(\Delta P_{t,z}^{Norm} - \hat{s}_0 - \hat{s}_1 \Delta T_{t,z} \right)^2 \tag{5}$$

where $\hat{s}_0$ and $\hat{s}_1$ are the estimated constant term of the regression model and the temperature sensitivity coefficient.

In the proposed method, the following temperature compensation with respect to the temperature sensitivity is used to forecast each daily peak load during the planning period of the DSM program:

$$\hat{P}_{t+1,d}^{k} = \hat{P}_{t+1} \left\{ 1 + \hat{s}_1 \left(\hat{T}_d^k - T_{base} \right) \right\} \tag{6}$$

where $\hat{P}_{y+1,d}^{k}$ and $\hat{T}_d^k$ are the adjusted peak load and the temperature on the $d-th$ day of the $k-th$ stochastic temperature path in the $t+1$ year.

3.2.4 24 Hourly load forecasting

To forecast the 24 hourly loads, this study uses a normalization technique. The normalized value of the 24-h loads is given by

$$P_{t,d,h}^{Avg\_pu} = \frac{1}{N} \sum_{k} \left(\frac{P_{t,k,h}}{P_{t,k}^{\max}} \right) \tag{7}$$

where $P_{t,d,h}^{Avg\_pu}$ is the average hourly load of the selected days at hour h in year t, $P_{t,k,h}$ and $P_{t,k}^{\max}$ are the hourly load and the peak load at hour h of day k in year t, and N is the number of observations in the historical data set obtained from the previous year.

The 24 hourly loads of the $d-th$ day of the $k-th$ stochastic temperature path in the t year are predicted using the following equation:

$$\hat{P}_{t,d,h}^{k} = \hat{P}_{t,d}^{k} \times P_{t,d,h}^{Avg\_pu} . \tag{8}$$

3.3 Probability estimation

The final stage of the proposed planning method is to calculate the DSM operating days, hours, and total capacity to meet the target peak load. The DSM operating days and hours can be calculated using a unit step function. The DSM operating days, hours, and total capacity of the $k-th$ stochastic temperature path are calculated with the following equations:

$$DSM_{Days}\left(k\right)=\sum_{d}U\left\{\max\left(\hat{P}_{t,d}^{k}-Target\ Peak\ Load,0\right)\right\} \quad (9)$$

$$DSM_{Hours}\left(k\right)=\sum_{d}\sum_{t=1}^{24}U\left\{\max\left(\hat{P}_{t,d,t}^{k}-Target\ Peak\ Load,0\right)\right\} \quad (10)$$

$$DSM_{Capacity}\left(k\right)=\sum_{d}\sum_{t=1}^{24}\max\left(\hat{P}_{t,d,h}^{k}-Target\ Peak\ Load,0\right). \quad (11)$$

When calculating the above, it is essential to eliminate weekend and holiday data in the planning period, otherwise these quantities may be overestimated.

The DSM operating days, hours, and total capacity obtained from a Monte-Carlo simulation can be modeled by the GEV distribution, which is suitable for modeling extreme or rare events [9, 10]. GEV combines the Gumbel, Fréchet, and Weibull extreme value distributions. From extreme value theory, the GEV distribution is the limit of the normalized maxima of a sequence of independent and identically distributed random variables. This model is widely used in risk management, finance, insurance, economics, hydrology, telecommunications, material sciences, and many other industries dealing with extreme events [11].

The general probability distribution function (PDF) and cumulative distribution function (CDF) for the GEV distribution are shown below:

$$f\left(x\mid\mu,\sigma,\xi\right)=\frac{1}{\sigma}\left[1+\xi\left(\frac{x-\mu}{\sigma}\right)\right]^{(-1/\xi)-1}\exp\left\{-\left[1+\xi\left(\frac{x-\mu}{\sigma}\right)\right]^{-1/\xi}\right\} \quad (12)$$

$$F\left(x\mid\mu,\sigma,\xi\right)=\exp\left\{-\left[1+\xi\left(\frac{x-\mu}{\sigma}\right)\right]^{-1/\xi}\right\} \quad (13)$$

for $1+\xi\cdot\left(\frac{x-\mu}{\sigma}\right)>0$, where μ, σ, and ξ denote the location, scale, and shape parameters.

In the proposed method, the expectation value and confidence interval of the operating days, hours, and total capacity for the incentive-based DSM program can be estimated by (12) and (13).

4. Numerical Results

In this section, the results of case studies are presented and analyzed to validate the effectiveness of the proposed method. The hourly load and weather data for the case studies were obtained from the Korea Power Exchange (KPX) and the Korea Meteorological Administration (KMA), respectively.

The peak load of the Korea Power System occurs in summer (July and August) and winter (December, January, and February). In this study, the DSM operating days, hours duration, and total capacity required to meet the target peak load, which is determined by the system operator or utility, is estimated for the summer season and compared with the actual value from 2012.

The proposed method uses the temperature stochastic process to estimate the probabilistic DSM operating days, hours, and total capacity. In this study, correlation analysis is adopted to identify the dominant temperature feature for data selection process. The tested temperature features include maximum temperature, minimum temperature, and average temperature. The dominant temperature feature is identified by evaluating Pearson correlation coefficient between these temperature features and maximum daily loads from season to season. Examples of the stochastic minimum temperature paths using equation (3), and real temperature in Seoul in summer season 2012 are shown in Fig. 3. The black line and gray lines are the actual daily minimum temperature and the twenty stochastic minimum temperature paths. This figure shows that the proposed temperature model is able to simulate the actual temperature volatility. In the case studies, 10,000 temperature paths were generated and used to derive the probabilistic DSM operating days, hours, and total capacity.

Daily peak loads of the planning period for the incentive-based DSM program are predicted using the base peak load and the temperature sensitivity using equations (1), (2), and (6). Fig. 4 shows the predicted base season-peak load and daily peak loads for one generated stochastic minimum temperature path in the summer season 2012.

Next, 24 hourly loads are predicted by multiplying each daily peak load and the normalized 24 hourly load pattern.

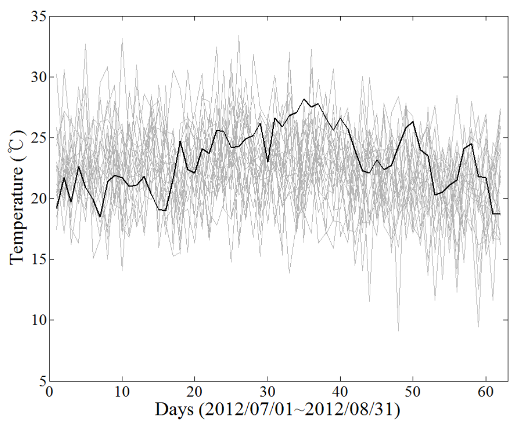

Fig. 3. Example of stochastic minimum temperature paths and actual minimum temperature in Seoul 2012

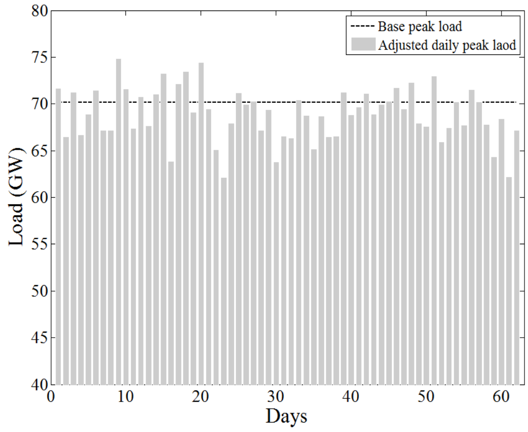

Fig. 4. Base peak load and adjusted daily peak load

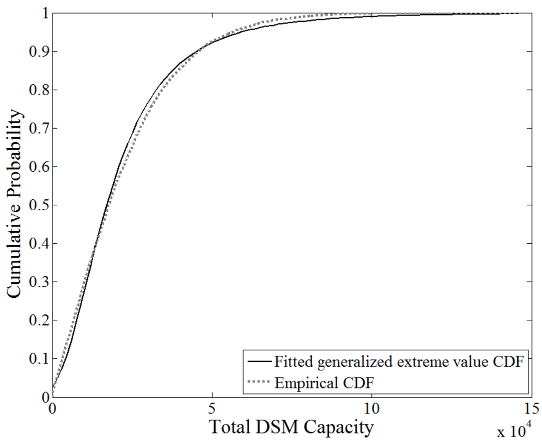

Fig. 5. CDF for total DSM capacity

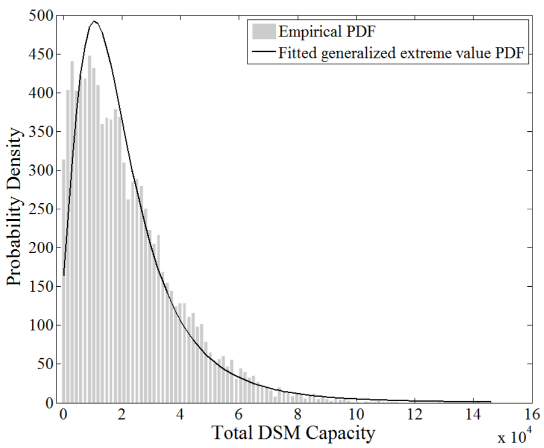

Fig. 6. PDF for total DSM capacity

Table 1. Comparison of detailed information for the incentive-based DSM program in the summer season 2012

DSM information	Actual data	Proposed method
Days (day)	9	6.92
Hours (hour)	33	15.88
Total capacity (MW)	21,483	21,609

Table 1 gives a comparison of the actual data with the estimated DSM operating days, hours, and total capacity obtained by the proposed method to meet the target peak load (the peak load of the same period in the previous year). In this case, the total capacity was very similar to the actual value. It can be concluded from these results that the proposed method provides effective estimates of the required DSM operating days, hours, and total capacity of the incentive-based DSM program. As well as stochastic values, the proposed method can provide deterministic values for planning the DSM program.

Figs. 5 and 6 illustrate the probability distribution of the total DSM capacity for the summer season 2012. The PDF and CDF of the total DSM capacity are quite similar to the GEV distribution. Using this probability distribution, the confidence intervals of the total DSM capacity required to meet the target peak load can be estimated. This information can help the utility and ISO to plan and operate an incentive-based DSM program.

5. Conclusion

DSM is one of the key technology elements to satisfy increasing electric demand without additional power system infrastructure.

This paper presents a stochastic method for planning the incentive-based demand side management program using load forecasting with the temperature stochastic process and the generalized extreme value distribution. The proposed method consists of three stages: data acquisition, load forecasting with stochastic simulation, and probability estimation. Numerical tests show the feasibility and the efficiency of the proposed method. The estimation results are tabulated and plotted for evaluation and comparison.

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