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Research Article

Planning of Electric Power Systems Considering Virtual Power Plants with Dispatchable Loads Included: An Inexact Two-Stage Stochastic Linear Programming Model

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In this study, an inexact two-stage stochastic linear programming (ITSLP) method is proposed for supporting sustainable management of electric power system under uncertainties. Methods of interval-parameter programming and two-stage stochastic programming were incorporated to tackle uncertainties expressed as interval values and probability distributions. The dispatchable loads are integrated into the framework of the virtual power plants, and the support vector regression technique is applied to the prediction of electricity demand. For demonstrating the effectiveness of the developed approach, ITSLP is applied to a case study of a typical planning problem of power system considering virtual power plants. The results indicate that reasonable solutions for virtual power plant management practice have been generated, which can provide strategies in mitigating pollutant emissions, reducing system costs, and improving the reliability of power supply. ITSLP is more reliable for the risk-aversive planners in handling high-variability conditions by considering peak-electricity demand and the associated recourse costs attributed to the stochastic event. The solutions will help decision makers generate alternatives in the event of the insufficient power supply and offer insight into the tradeoffs between economic and environmental objectives.

1. Introduction

Due to the shortage of fossil fuel and the resulting of environmental pollution problems from energy combustion, renewable energy power generation has caught worldwide attention. However, there are many challenges in the processes of environment-friendly power systems planning. The availabilities of renewable energy resources highly rely on natural and meteorological conditions, which may further intensify the complexity of the decision-making process. Many technologies and measures have been proposed to solve the instability of renewable energy power generation. Among them, virtual power plants (VPPs) is proposed as an innovative technology of the power system, and it can effectively integrate, aggregate, and manage both conventional and renewable energy power plants to achieve rational power allocation with limited and changeable resource availabilities [1–6]. VPPs refers to heterogeneous power plants, which usually include renewable energy power plants, traditional fossil–fuel-fired power plants, energy storage facilities, and dispatchable loads (shown in Figure 1). Through the coordination of the VPPs, the impact of fluctuations in renewable energy generation can be abated. Previously, there were few studies focused on the optimization model of power systems with consideration of VPPs with dispatchable loads. Furthermore, many economic, environmental, and political factors dynamically affect system planning processes, resulting in uncertainties in some key system parameters (e.g., renewable energy availability, load demands, and energy prices). These uncertainties and their latent interactions might further intensify the complexity of the decision-making process. Previous research on VPPs rarely considered these uncertainties.

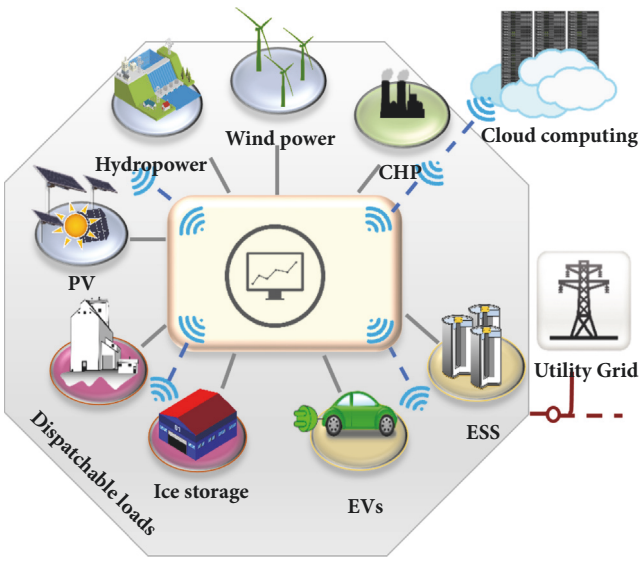

Figure 1: The composition of heterogeneous VPPs. Note. PVs: photovoltaic units; ESS: energy storage system; DLs: dispatchable loads; EVs: electric vehicles; CHP: combined heat and power.

Therefore, efficient mathematical programming techniques for planning electric power systems with consideration of uncertainties and complexities are desired.

Optimization techniques have played an important role in helping decision makers manage planning problems in an effective and efficient way [7–13]. In past decades, a multitude of optimization methods were proposed for dealing with electric power systems management problems. In these research work, some techniques were used to handle various uncertainties existing in the electric power systems. Among these techniques, stochastic programming (SP) have received extensive attention since they could directly integrate uncertain information expressed as probability distributions into the optimization framework. For example, Cai et al. [14] proposed an inexact chance-constrained community-scale energy model for long-term renewable energy management. Li et al. [15] developed an interval-parameter credibility constrained programming model for the electric power system planning and greenhouse gas (GHG) emission mitigation. Koltsaklis and Georgiadis [16] developed a stochastic multiregional multiperiod mixed-integer linear programming approach for Greek generation expansion planning.

Some limitation of the conventional SP methods is that they are incapable of considering the variability of the recourse values since it is assumed that the decision maker is risk neutral. However, the decision maker might be risk-averse under high-variability conditions. In fact, electric power systems are often associated with various system-failure risks (e.g., renewable energy supply risk) due to multiple uncertainties and unpredictable events. Desired energy allocation patterns might vary from time to time under high-variability conditions. Such unstable power supply might result in a high risk of electricity shortage, particularly when electricity demand-level is high. Two-stage stochastic programming (TSP) can take corrective actions after a random event occurs. In TSP, a first-stage decision is made before the occurrence of a random event, and then a second-stage decision can be made after the random events have happened. This could minimize losses that may appear due to any system failure [17–19]. However, TSP method could merely deal with uncertainties described in one single format. It has difficulties in addressing uncertainties existing in multiple levels, especially when knowledge is insufficient to obtain probability distributions. Interval programming (IP) can reflect interval information in the coefficients of the objective function and constraints, without knowing distribution information [20, 21]. Interval solutions can also be obtained in objective function and decision variables, which is helpful for decision makers to interpret and adjust decision schemes according to practical situations. Thus, TSP and IP can be integrated to enhance the capability of addressing multiple uncertainties in power system planning with VPPs.

Therefore, the objective of this study is to develop an inexact two-stage stochastic linear programming model for planning the electric power system including VPPs in a hybrid uncertain environment. ITSLP-VPP will integrate two-stage stochastic programming and interval-parameter programming in an energy system planning framework with consideration of virtual power plants. Results will provide the following decision support: (a) reflecting uncertain interactions among multiple random variables and disclosing their impacts on system outputs; (b) achieving tradeoffs between environmental conservation and system costs; (c) evaluating the economic impacts and CO_2 emission mitigation benefits of the energy scheme alternatives due to the introduction of VPPs.

This paper is organized as follows. Section 2 presents the development of ITSLP-VPP model. Section 3 introduces the basic structure of VPP and describes case studies and simulation results of electric power systems considering VPPs, where solutions under the different scenarios and uncertainty analysis are analyzed. Section 4 presents conclusions and future works.

2. Model Development

2.1. Interval Two-Stage Stochastic Linear Programming. Two-stage stochastic programming model can reflect the tradeoffs between pre-regulated policy and the associated economic penalty due to any infeasible event, and the fundamental concept includes recourse and adaptive adjustments. A general TSP model can be formulated as follows:

$$\min f = C^{\mathrm{T}} X + E_{\omega \in \Omega} [Q(X, \omega)] \tag{1a}$$

subject to

$$AX \geq B \tag{1b}$$

$$X \geq 0 \tag{1c}$$

where C is the vector of coefficients; X is the first-stage decision variable; ω is the random variable; $E[\bullet]$ is the expected value of the random variable; and the inequalities

(1b) and (1c) are constraints of the model, where A and B are technical coefficient. $Q(X,\omega)$ can be written as follows:

$$Q(X,\omega) = \min q(Y,\omega) \tag{1d}$$

$$D(\omega)\, y \geq h(\omega) + T(\omega)\, x \tag{1e}$$

$$\begin{aligned} &x \in X, \\ &y \in Y \end{aligned} \tag{1f}$$

where Y is the second-stage decision variable; $q(Y,\omega)$ denotes the second-stage cost function; and $\{D(\omega), T(\omega), h(\omega) \mid \omega \in \Omega\}$ are random model parameters corresponding to their dimensions; they are the functions of the random variable ω. By letting random variables (i.e., ω) take discrete values ω_h with probability levels p_h ($h = 1, 2, \ldots, v$ and $\sum p_h = 1$), Model (1a), (1b), (1c), (1d), (1e), and (1f) can be equivalently formulated as a linear programming model [22, 23].

$$\min f = C^{T_1} X + \sum_{h=1}^{v} p_h D^{T_2} Y \tag{2a}$$

subject to

$$A_r X \geq B_r, \quad r = 1, 2, \ldots, m_1 \tag{2b}$$

$$A_t X + A_t' Y \geq \omega_h, \quad t = 1, 2, \ldots, m_2 \tag{2c}$$

$$\begin{aligned} &x_j \geq 0, \\ &x_j \in X, \\ &\qquad j = 1, 2, \ldots, n_1 \end{aligned} \tag{2d}$$

$$\begin{aligned} &y_{jh} \geq 0, \\ &y_{jh} \in Y, \\ &\qquad j = 1, 2, \ldots, n_2,\ h = 1, 2, \ldots, v \end{aligned} \tag{2e}$$

where r is the number of general constraints and t is the number of constraints associated with the random variables.

Model (2a), (2b), (2c), (2d), and (2e) can effectively reflect uncertainties in resources (such as solar energy and wind energy) availability. An extended consideration is for uncertainties in the other parameters. For example, some economic data may not be available as deterministic values. In many practical problems, the quality of information that can be obtained for these uncertainties is mostly not good enough to be presented as probability distributions. Interval-parameter linear programming is efficient in coping with uncertain information expressed as interval numbers with known lower and upper bounds but unknown distribution functions. Based on the above consideration, interval parameters are introduced into the TSP framework to communicate uncertainties in technical coefficients into the optimization process. This leads to a hybrid inexact TSP (or ITSLP) model as follows:

$$\min f^{\pm} = C_{T_1}^{\pm} X + \sum_{h=1}^{v} p_h D_{T_2}^{\pm} Y^{\pm} \tag{3a}$$

subject to

$$A_r^{\pm} X^{\pm} \geq B_r^{\pm}, \quad r = 1, 2, \ldots, m_1 \tag{3b}$$

$$A_t^{\pm} X^{\pm} + A_t'^{\pm} Y^{\pm} \geq \omega_h^{\pm}, \quad t = 1, 2, \ldots, m_2 \tag{3c}$$

$$\begin{aligned} &x_j^{\pm} \geq 0, \\ &x_j^{\pm} \in X^{\pm}, \\ &\qquad j = 1, 2, \ldots, n_1 \end{aligned} \tag{3d}$$

$$\begin{aligned} &y_{jh}^{\pm} \geq 0, \\ &y_{jh}^{\pm} \in Y^{\pm}, \\ &\qquad j = 1, 2, \ldots, n_2,\ h = 1, 2, \ldots, v. \end{aligned} \tag{3e}$$

Model (3a), (3b), (3c), (3d), and (3e) can be transformed into two deterministic submodels that correspond to the lower and upper bounds of desired objective function value. This transformation process is based on an interactive algorithm, which is different from the best/worst case analysis [24, 25]. The submodel corresponding to the lower bound f^- should be first solved when the objective function is to minimize $f^{\pm}$ and can be formulated as follows:

$$\begin{aligned} \min f^- = &\sum_{j=1}^{k_1} c_j^- x_j^- + \sum_{j=k_1+1}^{n_1} c_j^- x_j^+ + \sum_{j=1}^{k_2} \sum_{h=1}^{v} p_h d_j^- y_{jh}^- \\ &+ \sum_{j=k_2+1}^{n_2} \sum_{h=1}^{v} p_h d_j^- y_{jh}^+ \end{aligned} \tag{4a}$$

subject to

$$\begin{aligned} &\sum_{j=1}^{k_1} \left|a_{rj}^{\pm}\right|^{+} \operatorname{sign}\left(a_{rj}^{\pm}\right) x_j^- \\ &\quad + \sum_{j=k_1+1}^{n_1} \left|a_{rj}^{\pm}\right|^{-} \operatorname{sign}\left(a_{rj}^{\pm}\right) x_j^+ \leq b_r^-, \quad \forall r \end{aligned} \tag{4b}$$

$$\begin{aligned} &\sum_{j=1}^{k_1} \left|a_{tj}^{\pm}\right|^{+} \operatorname{sign}\left(a_{tj}^{\pm}\right) x_j^- + \sum_{j=k_1+1}^{n_1} \left|a_{tj}^{\pm}\right|^{-} \operatorname{sign}\left(a_{tj}^{\pm}\right) x_j^+ \\ &\quad + \sum_{j=1}^{k_2} \left|a_{tj}^{\pm}\right|^{+} \operatorname{sign}\left(a_{tj}^{\pm}\right) y_{jh}^- \\ &\quad + \sum_{j=k_2+1}^{n_2} \left|a_{tj}^{\pm}\right|^{-} \operatorname{sign}\left(a_{tj}^{\pm}\right) y_{jh}^+ \leq \omega_h^-, \quad \forall t, h \end{aligned} \tag{4c}$$

$$x_j^- \geq 0, \quad j = 1, 2, \ldots, k_1 \tag{4d}$$

$$x_j^+ \geq 0, \quad j = k_1 + 1, k_1 + 2, \ldots, n_1 \tag{4e}$$

$$y_{jh}^- \geq 0, \quad j = 1, 2, \ldots, k_2;\ \forall h \tag{4f}$$

$$y_{jh}^+ \geq 0, \quad j = k_2 + 1, k_2 + 2, \ldots, n_2;\ \forall h. \tag{4g}$$

Based on the above solutions, the second submodel for f^+ can be formulated as follows:

$$\min f^+ = \sum_{j=1}^{k_1} c_j^+ x_j^+ + \sum_{j=k_1+1}^{n_1} c_j^+ x_j^- + \sum_{j=1}^{k_2}\sum_{h=1}^{v} p_h d_j^+ y_{jh}^+ + \sum_{j=k_2+1}^{n_2}\sum_{h=1}^{v} p_h d_j^+ y_{jh}^- \tag{5a}$$

subject to

$$\sum_{j=1}^{k_1} \left|a_{rj}^{\pm}\right|^- \operatorname{sign}\left(a_{rj}^{\pm}\right) x_j^+ + \sum_{j=k_1+1}^{n_1} \left|a_{rj}^{\pm}\right|^+ \operatorname{sign}\left(a_{rj}^{\pm}\right) x_j^- \le b_r^+, \quad \forall r \tag{5b}$$

$$\sum_{j=1}^{k_1} \left|a_{tj}^{\pm}\right|^- \operatorname{sign}\left(a_{tj}^{\pm}\right) x_j^+ + \sum_{j=k_1+1}^{n_1} \left|a_{tj}^{\pm}\right|^+ \operatorname{sign}\left(a_{tj}^{\pm}\right) x_j^- + \sum_{j=1}^{k_2} \left|a_{tj}^{\pm}\right|^- \operatorname{sign}\left(a_{tj}^{\pm}\right) y_{jh}^+ + \sum_{j=k_2+1}^{n_2} \left|a_{tj}^{\pm}\right|^+ \operatorname{sign}\left(a_{tj}^{\pm}\right) y_{jh}^- \le \omega_h^+, \quad \forall t, h \tag{5c}$$

$$x_j^+ \ge x_{j\,opt}^-, \quad j = 1, 2, \ldots, k_1 \tag{5d}$$

$$x_{j\,opt}^+ \ge x_j^- \ge 0, \quad j = k_1 + 1, k_1 + 2, \ldots, n_1 \tag{5e}$$

$$y_{jh}^+ \ge y_{jh\,opt}^-, \quad j = 1, 2, \ldots, k_2; \ \forall h \tag{5f}$$

$$y_{jh\,opt}^+ \ge y_{jh}^- \ge 0, \quad j = k_2 + 1, k_2 + 2, \ldots, n_2; \ \forall h. \tag{5g}$$

Therefore, the following solutions for the ITSLP Model (3a), (3b), (3c), (3d), and (3e) can be obtained:

$$f_{opt}^{\pm} = \left[f_{opt}^-, f_{opt}^+\right] \tag{6a}$$

$$x_{j\,opt}^{\pm} = \left[x_{j\,opt}^-, x_{j\,opt}^+\right] \tag{6b}$$

$$y_{jh\,opt}^{\pm} = \left[y_{jh\,opt}^-, y_{jh\,opt}^+\right]. \tag{6c}$$

2.2. Development of ITSLP-VPP Model. The decision makers are responsible for allocating electricity-supply patterns, capacity expansions, and pollutant mitigation with a minimum system cost over a mid-term planning horizon. Five types of electricity-conversion facilities are considered, namely, coal-fired and natural gas-fired plants, photovoltaic power, hydropower station, and wind power farm. In order to tackle such multiple formats of uncertainties in electric power systems considering virtual power plants, interval linear programming and two-stage stochastic programming methods are incorporated within a general planning model, leading to an inexact two-stage stochastic linear programming model. The objective of the model is to minimize the system cost, while a set of constraints are formulated to define the relationships among the system factors/conditions and decision variables. The ITSLP-VPP can be formulated as follows:

$$\min f^{\pm} = \min\left(f_1{}^{\pm} + f_2{}^{\pm} + f_3{}^{\pm} + f_4{}^{\pm}\right). \tag{7a}$$

The system cost includes the cost for energy resource purchase, the cost for electricity generation from conventional power plants and VPPs, and the cost for pollutant treatment. Due to the intermittent and unreliability of renewable energy power generation, the actual generation deviates from the planned generation. When random events occur, the dispatchable loads (such as large-scale ice storage, hot-spring facilities, and energy storage system) can be used as an important part of regulating power generation deviations. Therefore, deviation economic costs and the compensation costs of the dispatchable loads are included in the cost of power generation as the cost of the second-stage. In detail, the system cost is a sum of the following items:

(1) The Total Cost for Purchasing Primary Energy

$$f_1{}^{\pm} = \sum_{t=1}^{3}\sum_{k=1}^{2} AER_{t,k}^{\pm} \times CER_{t,k}^{\pm} \tag{7b}$$

(2) Fixed and Variable Generation Costs for Conventional Power Plants

$$f_2{}^{\pm} = \sum_{t=1}^{3}\sum_{s=1}^{4}\sum_{d=1}^{4}\sum_{i=1}^{2} AEG_{t,s,d,i}^{\pm} \times CVG_{t,i}^{\pm} + \sum_{t=1}^{3}\sum_{i=1}^{2} CFM_{t,i}^{\pm} \times ICA_{t,i}^{\pm} \tag{7c}$$

(3) Generation and Operating Costs of the VPPs

$$f_3{}^{\pm} = f_{3,1}{}^{\pm} + f_{3,2}{}^{\pm} \tag{7d}$$

where

$$f_{3,1}{}^{\pm} = \sum_{t=1}^{3}\sum_{s=1}^{4}\sum_{d=1}^{4}\sum_{j=1}^{3} AR_{t,s,d,j}^{\pm} \times CAR_{t,j}^{\pm} \tag{7e}$$

$$\begin{aligned} f_{3,2}{}^{\pm} &= \sum_{t=1}^{3}\sum_{s=1}^{4}\sum_{d=1}^{4}\left(E\left[GE_{t,s,d}^{(\omega)\pm}\right] \times CR_{t,s,d}^{\pm}\right) \\ &= \sum_{t=1}^{3}\sum_{s=1}^{4}\sum_{d=1}^{4}\left(\sum_{m=1}^{3} p_m\left(GEW_{t,s,d}^{(\omega)\pm} \times CRW_{t,s,d}^{\pm} + GES_{t,s,d}^{(\omega)\pm} \times CRS_{t,s,d}^{\pm} + GEH_{t,s,d}^{(\omega)\pm} \times CRH_{t,s,d}^{\pm} + ACS_{t,s,d}^{(\omega)\pm} \times CCS_{t,s,d}^{\pm}\right)\right) \end{aligned} \tag{7f}$$

(4) Pollutants Emission Costs

$$f_4^{\pm} = \sum_{t=1}^{3}\sum_{s=1}^{4}\sum_{d=1}^{4}\sum_{i=1}^{2} AEG_{t,s,d,i}^{\pm} \times cf_{t,i}^{\pm} \times \eta_{t,i}^{\pm} \times CCR_{t,i}^{\pm} \tag{7g}$$

subject to the following.

(1) Electricity Demand Constraints

$$\sum_{s=1}^{4}\sum_{d=1}^{4}\sum_{i=1}^{2} AEG_{t,s,d,i}^{\pm} + \sum_{s=1}^{4}\sum_{d=1}^{4}\sum_{j=1}^{3} AR_{t,s,d,j}^{\pm} \geq DM_t^{\pm} \times \left(1+\theta_t^{\pm}\right), \quad \forall t \tag{7h}$$

(2) Capacity Limitation Constraint for Power Generation Facilities

$$\sum_{s=1}^{4}\sum_{d=1}^{4}\sum_{i=1}^{2} AEG_{t,s,d,i}^{\pm} \leq \sum_{i=1}^{2} ICA_{t,i} \times STM_{t,i}^{\pm}, \quad \forall t \tag{7i}$$

(3) CO_2 Emission Constraints

$$\sum_{s=1}^{4}\sum_{d=1}^{4}\sum_{i=1}^{2} AEG_{t,s,d,i}^{\pm} \times cf_{t,i}^{\pm} \times \left(1-\eta_{t,i}^{\pm}\right) \leq EM_t, \quad \forall t \tag{7j}$$

(4) Electricity Peak-Load Demand Constraints

$$\sum_{i=1}^{2} AEG_{t,s,d,i}^{\pm} + \sum_{j=1}^{3} AR_{t,s,d,j}^{\pm} - GES_{t,s,d,m}^{(\omega)\pm} - GEW_{t,s,d,m}^{(\omega)\pm} - GEH_{t,s,d,m}^{(\omega)\pm} \geq PLOAD_{t,s,d}^{\pm} - ACS_{t,s,d,m}^{(\omega)\pm}, \quad \forall t, s, d \tag{7k}$$

(5) Renewable Energy Availability Constraints

$$\sum_{d=1}^{4}\left(AR_{t,s,d,1}^{\pm} + GEW_{t,s,d,m}^{(\omega)\pm} + GEH_{t,s,d,m}^{(\omega)\pm} - ACS_{t,s,d,m}^{(\omega)\pm}\right) \leq AVS_{t,s,m}^{(\omega)\pm}, \quad \forall t, s, m \tag{7l}$$

Electricity generated from solar energy equal to or less than its total availability

$$\sum_{d=1}^{4}\left(AR_{t,s,d,2}^{\pm} + GES_{t,s,d,m}^{(\omega)\pm} + GEH_{t,s,d,m}^{(\omega)\pm} - ACS_{t,s,d,m}^{(\omega)\pm}\right) \leq AVW_{t,s,m}^{(\omega)\pm}, \quad \forall t, s, m \tag{7m}$$

Electricity generated from wind energy equal to or less than its total availability

$$\sum_{d=1}^{4}\left(AR_{t,s,d,3}^{\pm} + GES_{t,s,d,m}^{(\omega)\pm} + GEW_{t,s,d,m}^{(\omega)\pm} - ACS_{t,s,d,m}^{(\omega)\pm}\right) \leq AVH_{t,s,m}^{(\omega)\pm}, \quad \forall t, s, m \tag{7n}$$

Electricity generated from hydropower equal to or less than its total availability

(6) Dispatchable Loads Regulation Constraints

$$\sum_{d=1}^{4} ACS_{t,s,d,m}^{\pm} \leq \sum_{d=1}^{4}\left(\frac{QCS_{t,s,d}^{\pm}}{COP_{t,s,d}^{\pm}}\right) \times ST_{t.s}^{\pm} \times TOR_{t,s}^{\pm}, \quad \forall t, s, m \tag{7o}$$

(7) Electricity Deficiency Equal to or Less Than the Predefined Targets

$$GES_{t,s,d,m}^{(\omega)\pm} + GEW_{t,s,d,m}^{(\omega)\pm} + GEH_{t,s,d,m}^{(\omega)\pm} + ACS_{t,s,d,m}^{(\omega)\pm} \leq \sum_{j=1}^{3} AR_{t,s,d,j}^{\pm}, \quad \forall t, s, d, m \tag{7p}$$

(8) Primary Energy Sources Availability Constraints

$$AER_{t,k}^{\pm} \leq UP_{t,k}, \quad \forall t, k \tag{7q}$$

$$\sum_{s=1}^{4}\sum_{d=1}^{4} AEG_{t,s,d,i}^{\pm} \times rf_{t,i}^{\pm} \leq AER_{t,k}^{\pm}, \quad \forall t, i \tag{7r}$$

(9) Nonnegativity Constraints

$$AEG_{t,s,d,i}^{\pm}, ACS_{t,s,d,m}^{(\omega)\pm}, AER_{t,k}^{\pm}, GES_{t,s,d,m}^{(\omega)\pm}, GEH_{t,s,d,m}^{(\omega)\pm}, GEW_{t,s,d,m}^{(\omega)\pm} \geq 0 \tag{7s}$$

The specific nomenclatures for variables and parameters are provided in Nomenclature. All the decision variables in the ITSLP-VPP model are considered as interval values.

The annual electricity demand forecast is an important part of power system planning, which is influenced by economic and social uncertainties. Support vector regression (SVR) can be applied to the prediction problem in the case of finite samples. Thus, SVR can be used for predicting electricity demand.

$$DM_t = \sum_{i=1}^{k}\left(\alpha_i^* - \alpha_i\right) K\left(x_i, x\right) + b^* \tag{8}$$

where α_i^*, α_i are the Lagrangian multipliers. $K(x_i, x)$ is called the kernel function, whose value equals the inner product of two vectors (such as x_i and x) in the feature space. b^* is constant. SVM aims to minimize the empirical risk. Selecting and determining the parameters of the kernel function require knowledge based on the application domain and reflect the distribution of the input training data as much as possible. There are many kernel functions commonly used, such as polynomial kernel function, Gaussian radial basis function (RBF), kernel function, and the Sigmoid kernel function. RBF kernel is easier to implement and able to nonlinearly map the training data into an infinite

dimensional space, and it is suitable to deal with nonlinear relationship problems. Thus, this study used RBF kernel to predict the electricity demand, radial basis function (RBF) with a width of σ : $K(x_i, x_j) = \exp(-\|x_i - x_j\|^2/2\sigma^2)$. SVR generalization performance depends on a good setting of regularization constant C, precision parameter ε, and the kernel parameters σ [26]. In this study, the optimal values of parameters C, ε, and σ are determined by employing a grid-search in a n-fold cross-validation approach which can prevent the overfitting problem [27, 28]. The mean absolute percent error (MAPE) is a commonly used forecasting error metric for quantifying and assessing the accuracy of the predicted output values. Meanwhile, the average relative error strengthens the function of the large error term in the indicator. Therefore, this study adopts the average relative error as the judgment basis of each prediction result. Three kinds of accuracy criteria (i.e., prediction accuracy: PA, Fitting accuracy: FA, and overall accuracy: OA) were used to assess the performance of the SVR model [26, 29, 30].

$$PA = 1 - \frac{\sum_{t=n+1}^{n+m} \left|\left(y_t - \hat{y}_t\right)/y_t\right|}{m} \times 100\% \tag{9a}$$

$$FA = 1 - \frac{\sum_{t=1}^{n} \left|\left(y_t - \hat{y}_t\right)/y_t\right|}{n} \times 100\% \tag{9b}$$

$$OA = 1 - \frac{\sum_{t=1}^{n+m} \left|\left(y_t - \hat{y}_t\right)/y_t\right|}{n+m} \times 100\% \tag{9c}$$

PA is used to compare actual electricity consumption values and predicted electricity consumption values during the test period. *FA* is used to compare the actual electricity consumption values and the predicted electricity consumption values of all the training points time periods. *OA*is used to compare actual electricity consumption values and to predict electricity consumption values over all time periods, including training and testing time periods.

3. Case Study and Result Analysis

To demonstrate its advantages, the proposed ITSLP-VPP method is applied to a case study of a typical regional electric power systems management problem with representative cost and technical data within a Chinese context.

3.1. Overview of the Study System. Renewable energy (e.g., hydro, wind, and solar) is naturally replenished and much more sustainable and cleaner in contrast with fossil fuels. Nevertheless, wind and solar power could not provide continuous power supply to end-users without backup power generation facilities or energy storage, due to intermittence of input energy, instability of weather condition, and flaw of technical restriction. Large-scale ice storage (LIS), freezers in supermarkets, or refrigerators and freezers in private homes can be viewed as storage electrical power facilities that store electricity in cold form. Hot-spring convalescent facilities using cogeneration systems store electricity in hot form, and electric cars in cities can also be used as energy storage devices in the Smart Grid. These facilities all have sponge-like properties; they can play a role of energy storage when the power load is at a low point (i.e., the generating capacity is higher than the load), absorbing and storing electricity, and when the load is at a peak period (i.e., the generating capacity is less than the load); it is like energy storage device that begins to release electricity, such as ice storage; even if the power is cut off, the temperature drop is very slow, in a certain temperature and time range, and will not lead to the deterioration of the quality of storage goods. When the wind power is strong, solar energy is abundant, and electricity market price is low, the smart control system can start the ice storage or reduce the set temperature of refrigerated in operation, to store a certain amount of electricity in 'cold' form. In the period of electricity shortage, lack of wind or solar energy, and high price in the electricity market, smart system can suspend the operation of ice storage, run the frequency converter, or increase the set temperature, to reduce the power consumption and play the role of peak-load shifting. Therefore, this study combines the LIS and renewable energy power plants to form virtual power plants. In the power shortage periods, the VPPs in some special areas can play an active role in regulation, such as areas having high reliance on renewable energy sources and port cities that have numerous LIS bases.

For each power-conversion technology, an electricity-generation target is preplanned. If the target is not exceeded, the system will encounter the regular costs; otherwise, the system will be subject to costs for the extra operation and maintenance, or the compensation costs of the dispatchable loads. The problems under consideration include (1) how to achieve the minimized total system cost with potential low carbon emissions, (2) how to assign scientific electricity-generation schemes, (3) how to deal with the uncertainties and random information existing in both the objective and constraints, and (4) how to identify the effective scheme of the dispatchable loads in the virtual power plant to achieve potential low carbon emissions and low system cost. A variety of uncertainties exist in these problems, increasing the complexity of the decision-making process. ITSLP-VPP is considered to be a promising approach for dealing with this electric power system management problem.

3.2. Data Collection and Result Analysis. Table 1 contains part of attributes for SVR prediction. The increasing power consumption in cities can be attributed to industrial development, economic improvement, and population growth. The first, second, and tertiary industry and industrial products are the main factors determining the use of electricity. Gross domestic product (GDP) is a broad parameter that reveals the prosperity of the urban economy, which provides a quantitative indicator of the average living standard, indicating the capacity to produce and consume electricity. We refer to the historical data of an administrative area and establish the analog input data of the model. Table 2 provides the costs for electricity generation expressed as interval values.

Figure 2 presents the observation, prediction, and error of electricity demand of the administrative district. Three kinds of accuracy criteria (i.e., PA, FA, and OA) were used to assess the performance of the SVR model, and the SVR parameters can be searched by the grid-search method. When the values

Table 1: The attributes for SVR prediction.

GDP (10^2million \$)	Primary industry (10^2million \$)	Secondary industry	Tertiary industry	Industry	Electricity consumption (10^2GWh)
42.82	2.79	23.82	16.2	21.50	67.24
78.19	3.39	39.69	35.12	36.11	70.97
88.17	3.62	44.06	40.49	39.93	75.14
98.81	3.87	49.12	45.83	44.49	84.30
118.44	4.13	61.44	52.88	55.95	93.90
142.92	4.84	77.45	60.63	71.19	105.29
179.43	5.16	98.09	76.18	89.95	115.45
205.03	4.75	112.88	87.40	103.90	130.10
241.32	5.06	132.89	103.37	122.29	148.41
308.68	5.63	170.44	132.62	157.07	154.77
345.57	5.92	183.21	156.44	166.41	165.05
423.79	6.69	222.37	194.73	202.64	193.72
519.48	7.34	272.36	239.78	249.50	208.55
592.37	7.88	306.15	278.34	281.30	222.96
663.49	8.66	335.75	319.09	307.19	238.34
722.52	9.18	355.22	358.12	325.23	247.18
759.79	9.59	353.95	396.26	320.80	255.34

Table 2: Cost for power generation.

	Period 1	Period 2	Period 3
Cost for purchasing fossil fuels (10^3\$/TJ)			
Coal	[0.32,0.38]	[0.30,0.36]	[0.28,0.34]
Natural gas	[0.35,0.42]	[0.33,0.40]	[0.31,0.38]
Variable cost for power generation (10^3\$/GWh)			
Coal	[1.62, 1.87]	[1.54,1.78]	[1.46,1.69]
Natural gas	[2.19,2.52]	[2.08,2.39]	[1.98,2.27]
Solar	[4.90,5.10]	[4.66,4.84]	[4.42,4.60]
Wind	[8.64,9.19]	[8.21,8.68]	[7.8,8.19]
Hydro	[6.58,7.80]	[6.25,7.41]	[5.94,7.03]

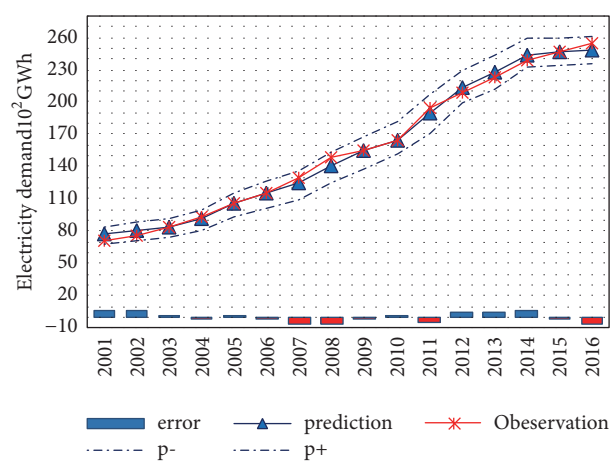

Figure 2: Comparison of the prediction and actual value with a SVR model.

of the parameters C, ε, and σ are 2^7, 2^{-7}, and 1.0 respectively, the PA, FA, and OA values of the SVR model are 95.42%, 91.36%, and 93.53%, respectively, and the predicted results are satisfactory. The predicting values of electricity demand are 263.34, 274.69, and 286.04 (10^2 GWh) from 2017 to 2019. p- is prediction -ε. p+ is prediction +ε. The forecast results are used to set the interval of electricity demand. Figure 3 shows the power generation of various generating technologies in the three study periods (corresponding to f^-). Over the planning horizon, the coal-fired power supply would gradually decline, but due to its high availability and competitive price, it still plays an important role in the power system. For example, during the spring, when d=1, the total coal-fired generation would be 1307,1166.82, and 1102 GWh in three periods, respectively. Likewise, the results during other times and seasons can be analyzed similarly to those. Renewable energy generation steadily increases during the planning periods. For instance, when d=1, wind power generation over the four seasons would be 360, 408.67, and 466.13 GWh in spring; 396, 447.55, and 497.3 GWh in summer; 396, 447.55, and 508.9 GWh in autumn; and 396, 447.55, and 508.9 in winter, respectively. Similarly, the obtained results of other power generation technologies can be interpreted. In addition, the power consumption of businesses and residents has changed a lot in 24 hours a day. The overall average load during summer high demand period and peak demand period was 29.36% higher than that in the general period. It would lead to the increase of electricity supply during high demand period and peak demand period (i.e., d=3, d=4). For example, hydropower supply in period 3 would rise from 84.17 GWh when d=3 to 148.32 GWh when d=4, which would be higher than 41.33 GWh when d=1 and 40.03 GWh when d=2. Moreover, renewable energy generation in the summer is

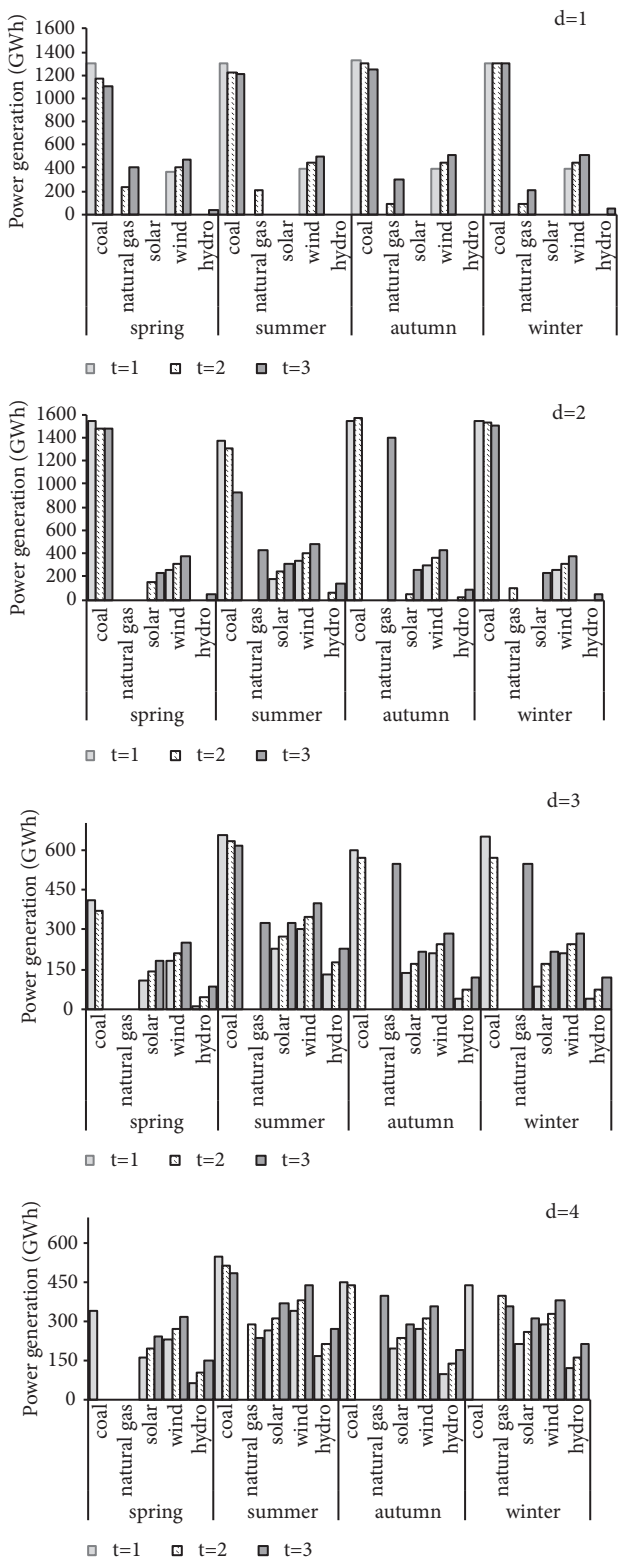

Figure 3: Power generation of various generating technologies in different periods (f^{-}).

higher than other seasons. This is related to the climate of the area corresponding to the reference data. Therefore, renewable energy generation arrangements have increased.

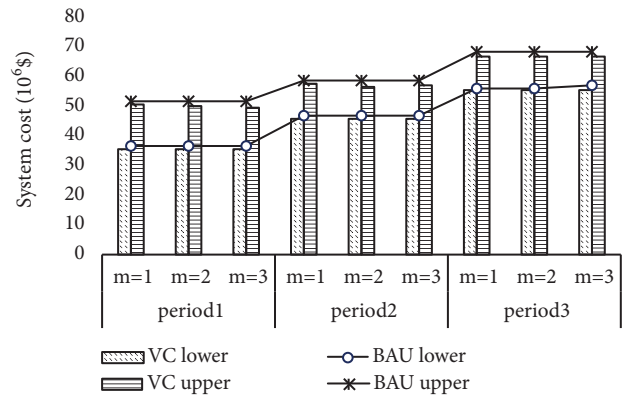

Figure 4: Comparison of expected costs between two scenarios. Note. BAU: business as usual; VC: VPP case.

On the other hand, with the decline of thermal power, in three planning periods, renewable energy generation proportion gradually increased, accounting for the total generation of 32.73%, 40.78%, and 42.67%.

Table 3 shows the dispatchable loads regulation amount under different renewable energy availability levels. The high, medium, and low resource availability levels correspond to m=1, m=2, and m=3, respectively. During different seasons, when the electricity-generation pattern varies under different m levels and within interval solution ranges, the dispatchable loads regulation amount would also fluctuate within its solution range correspondingly, which would be [0.43,58.08] GWh. The results show that the VPP's adjustable electricity is quite different at different times of different seasons. For example, when d = 4, the dispatchable load in VPP is only regulated in winter (50.16 GWh). This is because, unlike other seasons, the outdoor temperature in winter is low, and even if a part of the power of refrigeration equipment of LIS is cut off, the temperature drop would be very slow. The operation of the refrigeration equipment can be more flexibly started or stopped in a temperature range where the quality of stored goods does not deteriorate. Therefore, the dispatchable loads can play a considerable role in regulation during various time periods in winter. In comparison, the impact of the availability of renewable energy on the amount of regulation of controllable loads is less pronounced than that of seasons and time periods. For instance, during spring 1st time period, the amounts of electricity regulation are almost the same under the three m levels, which would be [47.38, 58.08], [47.38, 58.08], and [47.38, 50.16] GWh, respectively. Nevertheless, when the availabilities of renewable energy resources are insufficient to meet the energy demand, the LIS in VPP can play a positive regulatory role. The maximum ratio of LIS regulation to power generation shortage during the three planning periods is 94.16%, the minimum is 15.01%, and the average is 39.13%.

Figure 4 compares the system cost corresponding to BAU (business as usual, i.e., no dispatchable loads being included) and VC (VPP case) scenarios over the planning horizon. The power generation cost of the VC scenario is slightly lower than that of BAU. The system costs obtained from

Table 3: Dispatchable loads adjusting quantity.

Time	Period	p=1	p=2	p=3
Spring				
1	t=1	[47.38,58.08]	[47.38,58.08]	[47.38,50.16]
	t=2	[0,47.38]	[0,47.38]	[0,47.38]
	t=3	[0.43,20]	[0,0.43]	[0,0.43]
2	t=1	[0,50.16]	[0,50.16]	[0,50.16]
	t=2	[0,58.08]	[0,58.08]	[0,58.08]
	t=3	[27.38,57.65]	[38.08,57.65]	[13.85,57.65]
3	t=1	[0,57.65]	[0,57.65]	[0,57.65]
	t=2	0	0	0
	t=3	0	0	0
4	t=1	0	0	0
	t=2	0	0	0
	t=3	0	0	0
Summer				
1	t=1	[0,58.08]	[47.38,58.08]	0
	t=2	[0,58.08]	[0,58.08]	[47.38,58.08]
	t=3	[0,43.2]	[43.2,47.38]	[0,43.2]
2	t=1	[0,47.38]	0	[0,47.38]
	t=2	[0,47.38]	[0,47.38]	0
	t=3	[0,14.88]	[0,14.88]	[14.88,43.76]
3	t=1	[0,58.08]	[0,58.08]	[0,58.08]
	t=2	[0,58.08]	[0,58.08]	[0,58.08]
	t=3	[0,47.38]	0	0
4	t=1	0	0	0
	t=2	0	0	0
	t=3	0	0	0
Autumn				
1	t=1	0	0	0
	t=2	[0,22.36]	0	0
	t=3	[0,20]	0	0
2	t=1	[47.38,49.84]	47.38,49.84]	47.38,49.84]
	t=2	[25.02,58.08]	[47.38,58.08]	[47.38,58.08]
	t=3	[0,27.38]	[0,47.38]	[0,47.38]
3	t=1	[0,58.08]	[0,58.08]	[0,58.08]
	t=2	0	0	0
	t=3	[0,58.08]	[0,58.08]	[0,58.08]
4	t=1	0	0	0
	t=2	0	0	0
	t=3	0	0	0
Winter				
1	t=1	[47.38,58.08]	[47.38,58.08]	[0,47.38]
	t=2	[47.38,58.08]	[47.38,58.08]	[0,47.38]
	t=3	0	0	[0,20]
2	t=1	0	0	[0,58.08]
	t=2	0	0	[0,58.08]
	t=3	[0,7.38]	[0,47.38]	[27.38,58.08]
3	t=1	0	0	0
	t=2	0	0	0
	t=3	[0,40]	0	0
4	t=1	0	0	0
	t=2	[0,50.16]	[0,50.16]	[0,50.16]
	t=3	0	0	0

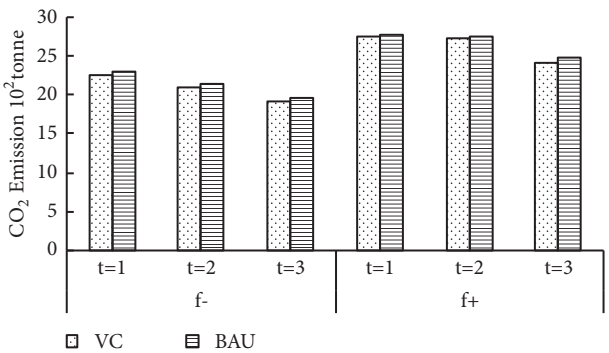

Figure 5: Carbon dioxide emissions in different scenarios.

these two scenarios would both increase with the planning period changes. For example, under VC scenario, when p=3, the total system cost for the three planning periods would be [35.41, 49.48], [45.47, 56.67], and [55.41, 66.63]×10^6\$, respectively. The solution results are lower than the system costs obtained for the BAU scenario, which are [36.41, 51.34], [46.47, 58.42], and [56.96, 68.34]×10^6\$, respectively. Similarly, the results under other m levels (m=1 and m=2) can be interpreted. In the optimal scheme of interval solution, the system cost of the VC scenario would be decreased at least by 1.98% lower than the BAU scenario, the highest is 3.63%, and the average decrease is 2.34%. The cost decline is not obvious because the scale of the dispatchable loads in the case is limited. With the development of energy Internet technology, the increase of the proportion of dispatchable loads is expected to bring more cost reduction space for the electric power system.

Figure 5 shows a comparison of carbon dioxide emissions conventional from conventional power generation scenario and from dispatchable loads as alternative scenarios in VPP. In detail, the BAU scenario leads to slightly higher CO_2 emissions than the VC scenario under all levels. The CO_2 emissions from BAU scenario are [23.13, 27.84]×10^6ton in period 1, [21.38, 27.65]×10^6ton in period 2, and [19.53, 24.84] 10^6ton in period 3. In comparison, the VC scenario would lead to the lower CO_2 emissions ([22.47, 27.65], [20.93, 27.34], [19.07, 24.23]×10^6ton, respectively). When the availabilities of renewable energy resources are limited, more electricity would be generated from conventional facilities, leading to higher CO_2 emissions. In comparison, the dispatchable loads in VPP can adjust its own electricity demand during these periods, shift to other time periods, and therefore lead to less CO_2 emissions. In addition, increasingly stringent emission limits would lead to a drop in overall emissions levels. For example, under VC scenario (corresponding to f^-), the CO_2 emissions would decrease from 22.47 10^6ton in period 1 to 20.93 10^6ton in period 2 and reach 19.07 10^6ton in period 3. The VC scenario may be of more interest to decision makers due to its lower system cost and CO_2 emissions.

The solutions obtained from the above two cases (BAU and VC) could provide useful decision alternatives under different policies and various energy availabilities. Compared with the BAU model, the ITSLP-VPP model could be an effective tool for providing environmental management schemes under various system conditions.

4. Conclusions

An inexact two-stage stochastic linear programming approach is developed for optimal electric power systems management with VPP under uncertainties. In the developed model, two-stage stochastic programming is incorporated into a two-stage programming optimization framework. The obtained results are useful for supporting electric power system management. The ITSLP-VPP approach is capable of (a) adjustment or justification of allocation patterns of renewable energy resources and services; (b) evaluation of the impact of intermittency of the renewable energy on the power system management; (c) decision support of local policies on energy use, economic development, and energy structures; (d) analysis of the interaction between economic costs, system reliability, and energy supply shortages.

This study attempts to develop a modeling framework for optimization problems involving uncertainties to deal with the electric power systems management problem with VPP. In the future practice, the proposed method could be further improved through considering more impact factors, for instance, the stability of the smart composite system, the peak-shaving risk caused by the uncertainty of the forecast of wind power and PV power generation, the effect of price-based policy and the incentive policy on the flexible response of VPP, and the integration of energy storage facilities.

Nomenclature

t:	Period (1 year for each period, t=1,2,3)
i:	Resource type, including coal and natural gas (i=1,2)
j:	Renewable energy generation type, including Solar, wind power, and hydro (j=1,2,3)
s:	Season, namely, spring, summer, autumn, or winter (s=1,2,3,4)
m:	The availability level of renewable energy (m=1 high, m=2 medium, and m=3 low.)
d:	Time (where d=1 for the trough period, a total of 8 hours (23:00-7:00); d=2 for the general period, 8 hours (7:00-8:00 and 11:00-18:00); d=3 (8:00-10:00,18:00-19:00, and 21:00-23:00); d=4 (10:00-11:00 and 19:00-21:00), respectively, the high demand period and peak demand period, 4 hours)
$AER^{\pm}_{t,k}$:	The supply of fossil fuels k for the generation in period t(TJ)
$AEG^{\pm}_{t,s,d,i}$:	Electricity-generation amount via electricity-generation technology i in period t season s time d

$AR^{\pm}_{t,s,d,j}$: The target for electricity generation from renewable energy j under season s time d period t that is determined at the first stage, which is the first-stage decision variable (GWh)
$ACS^{\pm}_{t,s,d}$: The amount of the dispatchable loads (GWh)
$AVH_{t,s,m}$: Availability of hydropower in period t season s under probability level m (GWh)
$AVS_{t,s,m}$: Availability of photovoltaic power in period t season s under probability level m (GWh)
$AVW_{t,s,d}$: Availability of wind power in period t season s under probability level m (GWh)
$CER^{\pm}_{t,k}$: Cost of purchasing primary energy k in period t (10^3\$/TJ)
$CVG^{\pm}_{t,i}$: Variable cost for generating electricity via electricity-generation technology i in period t (10^3\$/GWh)
$CFM^{\pm}_{t,i}$: Fixed cost for generating electricity via electricity-generation technology i in period t (10^3\$/GWh)
$CAR^{\pm}_{t,j}$: Average cost for renewable energy j electricity production when energy is sufficient (10^3\$/GWh)
$CR^{\pm}_{t,s,d}$: Average recourse cost for the shortage of electricity production (10^3\$/GWh)
$CRS^{\pm}_{t,s,d}$: Average recourse cost for the shortage of electricity production from solar energy (10^3\$/GWh)
$CRH^{\pm}_{t,s,d}$: Average recourse cost for the shortage of electricity production from hydropower (10^3\$/GWh)
$CRW^{\pm}_{t,s,d}$: Average recourse cost for the shortage of electricity production from wind energy (10^3\$/GWh)
$CCS^{\pm}_{t,s,d}$: Compensation cost of dispatchable loads (10^3\$/GWh)
$CCR^{\pm}_{t,i}$: Cost of pollution mitigation of power generation technology i in period t (10^3 \$/ton)
$COP^{\pm}_{t,s,d}$: Coefficient of performance of ice storage (BTU/GWh)
$DM^{\pm}_{t}$: Total electricity demand in period t (GWh)
EM_t: The maximum permitted CO_2 emission in period t (10^3 ton)
$GE^{\pm}_{t,s,d}$: The amount of renewable energy by which the target of AR is not met in period t, which is the second-stage decision variable (GWh)
$GES_{t,s,d}$: The amount of solar energy by which the target of AR is not met in period t (GWh)
$GEW_{t,s,d}$: The amount of wind energy by which the target of AR is not met in period t (GWh)
$GEH_{t,s,d}$: The amount of hydropower by which the target of AR is not met in period t (GWh)
$ICA^{\pm}_{t,i}$: The current capacity of power generation technology i in period t (GW)
$PLOAD^{\pm}_{t,s,d}$: Peak-load electricity demand (GWh)
$QCS^{\pm}_{t,s,d}$: Cooling capacity of ice storage during period d of the typical day in season s (BTU/h)
$STM^{\pm}_{t,i}$: Maximum service time of electricity-generation technology i in period t (hour)
$ST^{\pm}_{t.s}$: Average running time of ice storage
$TOR^{\pm}_{t,s}$: Maximum tolerated cooling deficiency rate
$UP_{t,k}$: Available resource k in period t
$cf^{\pm}_{t,i}$: Carbon dioxide emission coefficient
$\eta^{\pm}_{t,i}$: CO_2 emission factor in period t (10^3 ton/GWh)
$\theta^{\pm}_{t}$: Transmission loss in period t
$rf^{\pm}_{t,i}$: Energy consumption rate of electricity-conversion technology i.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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