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An optimization model for regional micro-grid system management based on hybrid inexact stochastic-fuzzy chance-constrained programming

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ABSTRACT

Micro-grid system management considering air pollutant control and carbon dioxide (CO_2) mitigation is a challenging task, since many system parameters such as electric demand, resource availability, system cost as well as their interrelationships may appear uncertain. To reflect these uncertainties, effective inexact system-analysis methods are desired. In this study, a hybrid inexact stochastic-fuzzy chance-constrained programming (ITSFCCP) was developed for micro-grid system planning, and interval-parameter programming (IPP), two-stage stochastic programming (TSP) and fuzzy credibility constrained programming (FCCP) methods were integrated into a general framework to manage pollutants and CO_2 emissions under uncertainties presented as interval values, fuzzy possibilistic and stochastic probabilities. Moreover, FCCP allowed satisfaction of system constraints at specified confidence level, leading to model solutions with the lowest system cost under acceptable risk magnitudes. The developed model was applied to a case of micro-grid system over a 24-h optimization horizon with a real time and dynamic air pollutant control, and total amount control for CO_2 emission. Optimal generation dispatch strategies were derived under different assumptions for risk preferences and emission reduction goals. The obtained results indicated that stable intervals for the objective function and decision variables could be generated, which were useful for helping decision makers identify the desired electric power generation patterns, and CO_2 emission reduction under complex uncertainties, and gain in-depth insights into the trade-offs between system economy and reliability.

Introduction

Electric power industry provides basic power for human activities and economic growth, and plays an essential role in social development. At the meantime, it is also a major source of carbon dioxide, sulfur dioxide, and nitric oxide (e.g. CO_2, SO_2, and NO_x) emissions. Especially, the environmental pollution caused by traditional fossil generation becomes a serious problem, which gains more social concern accurately. With the ever-increasing energy demand, electric system develops fast and traditional fossil generation still constitutes a high proportion of electricity market. With increasing globe awareness of environmental protection, effective generation scheduling has been extensively discussed to reduce greenhouse gas and air pollutants emission. On the other hand, under the pressure of both resources and environment, renewable energy generation has become more and more popular. Many countries have set up the goals of renewable resources generation plan for future grid construction. Due to its advantages of convenience, flexibility and environmental friendly, micro-grid providing better platform for renewable energy generation has become popular and important in modern electricity system [1,2].

In order to deal with the interrelated and complex problems in the development of modern electric power system, many great efforts have been made on the optimal generation scheduling. Compared with historical researches, which mainly focus on thermoelectric power generators, most of recent studies are about

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micro-grid and distributed generation with renewable resources. For example, Yazawa and Shakouri (2013) analyzed the energy cost and optimization of thermoelectric power generators, which shows a lower initial cost compared with commercialized micro gas turbines but higher operating cost per energy due to moderate efficiency [3]. Guo et al. (2012) advanced the optimal generation dispatch with wind power generation and coal-fired generation embedded, and the optimal dispatch model was solved by a particle swarm optimization algorithm on an IEEE 30-bus system [4]. Moreover, the optimal goal has changed from simply minimizing cost or maximizing profit into multi objective optimization like minimizing carbon emissions and violation risks of uncertainties. Since those goals are usually conflict, the Pareto-optimal solutions are desired by decision makers. Considering variable penalty policy for CO_2 emission, Tang and Che (2013) developed mixed integer nonlinear programming model to deal with the economic dispatch problem of thermal generation [5]. In the study by Buayai et al. (2012), the objective functions include real power loss, load voltage deviation and annualized investment cost, a pareto based non-dominated sorting genetic algorithm II was proposed to determine locations and sizes of the distributed generator units within micro-grid [6].

In fact, the electric system is extremely complex facing various uncertainties in generation side, demand side and market environment, which brings great challenge to the reliability of the electricity system [7–12]. As a result, relative research and on site projects are being carried out with a growing trend, a series of uncertainty methods have been proposed [13–20]. Among these methods, Two-stage stochastic programming (TSP) is a potential uncertainty technology and widely applied in electric generation planning and dispatch. Considering the power generation in a hydro-thermal generation system under uncertainty in demand and prices of fuel and delivery contracts, Nurnberg and Romisch (2002) developed a two-stage stochastic programming model for the short- or mid-term cost-optimal electric power production planning [21]. Nowak (2005) adopted a two-stage stochastic integer model for the simultaneous optimization of power production and day-ahead power trading [22]. Considering renewable energy generation, Hendrik van der Weijde (2012) developed cost-minimising TSP model and estimated the cost of ignoring uncertainty [23]. Combined with interval-parameter programming (IPP), TSP method was further developed into interval two-stage stochastic programming (ITSP) method, which can deal with uncertain optimization by interval and random numbers [24].

The traditional TSP or ITSP method cannot only provide an effective tool for energy policy scenarios analysis, but also handle the uncertain issue with certain probability [25,26]. However, in distributed energy generation system, the forecasting load of wind and solar power are usually obtained based on numerical weather prediction, which belongs to fuzzy information. If take them as deterministic parameters, it might easily mislead or bias the decision makers and lead to resource waste. In order to deal with the vague and obscure information, fuzzy set theory has provided a convenient formalism for classifying available renewable energy sources conditions. Fuzzy credibility constraints programming (FCCP) was proposed recently as a measure of confidence level in fuzzy environment to tackle uncertainties expressed as fuzzy sets. It was recognized as a competent measure of the confidence level regarding fuzzy constraints in optimization models [27,28]. Compared with other fuzzy programming approaches, the FCCP has a relatively low computational requirement and can obtain a series of solutions leading to high system benefits at allowable violation risk levels [29,30]. FCCP has been applied to many real-world cases due to its simplicity and efficiency in reflecting the fuzziness inherited with parameters associated with subjective consideration. Xue et al. (2012) developed an optimization model based on fuzzy credibility constraints programming for micro-grid operation with the uncertainties related to load and wind speed into consideration [31]. Based on mixed integer programming and FCCP, Zhang et al. (2012) developed integer fuzzy credibility constrained programming (IFCCP) to minimize the total cost of an independent regional power system [32]. Xu and Zhuan (2012) studied the optimization of wind power capacity for an electric power system with the system operation, economy and reliability emphasized, which is addressed by the FCCP approach [33]. Nevertheless, few previous studies were focused on development of inexact two-stage stochastic credibility constrained programming method through integrating IPP, TSP and FCCP into a general framework for electric schedule management within considering the pollutants and CO_2 emission control.

Therefore, the objective of this study is to develop an inexact stochastic-fuzzy chance-constrained optimization model for electric schedule management. Interval-parameter programming, two-stage stochastic programming and fuzzy credibility constrained programming methods are integrated into a general framework to manage pollutants and CO_2 emissions under uncertainties presented as interval values, fuzzy possibilistic and stochastic probabilities. It shows the impact for accounting for both risk-averse and emission reduction goal in a two-stage stochastic optimization model. Within this framework, a new formulation is proposed to determine the operation of traditional and renewable resources generation over a 24-h optimization horizon with both economic and environmental considerations, where pollutant management should follow a real time and dynamic control strategy, and total amount control for CO_2 emission.

The remaining sections of this paper are organized as follows: Section "Methodology" introduces the main theory of interval two-stage stochastic programming and credibility constrained programming. The framework of electric system operation with wind and photovoltaic power is presented in Section "Case study". A case study and results analysis are illustrated in Section "Results analysis and discussion". Finally, some conclusions are provided in Section "Conclusion".

Methodology

A hybrid inexact stochastic-fuzzy chance-constrained programming (ITSFCCP) model was based on interval-parameter programming, two-stage stochastic programming, and fuzzy credibility constraints programming (as shown in Fig. 1). Each technique has its unique contribution in enhancing the ITSFCCP's capacities for tackling the uncertainties and making the trade-offs between system economy and reliability. For example, in micro-grid system, the interval two-stage stochastic programming is used to reflect the uncertainty of energy market and technical parameters that expressed as intervals and the random characteristics of electric demand that expressed as stochastic numbers; and the system risk and the fuzzy availability of renewable energy sources were reflected through FCCP.

Interval two-stage stochastic programming

Two-stage stochastic programming (TSP) is effective for addressing problems where an analysis of policy scenarios is desired periodically over time and uncertain parameters are expressed as probability distribution functions (PDFs). A general TSP model can be formulated as follows [34]:

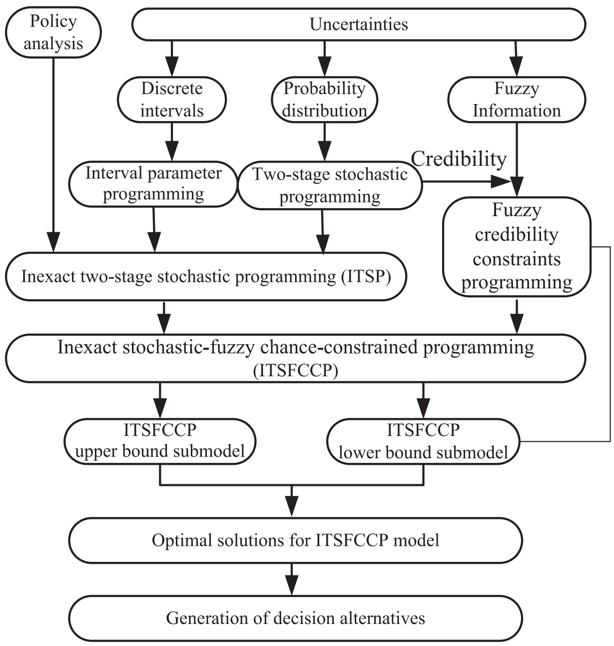

Fig. 1. Schematic diagram of ITSFCCP model.

$$\min \quad f = c^T x + \sum_{s=1}^{N} p_s Q(y, \omega_s) \tag{1a}$$

$$\text{subject to}: \quad ax \leqslant b \tag{1b}$$

$$T(\omega_s)x + W(\omega_s)y = h(\omega_s) \tag{1c}$$

$$x \geqslant 0, y(\omega_s) \geqslant 0 \tag{1d}$$

where x is vector of first-stage decision variables; $c^T x$ is first-stage benefits; ω is random events after the first-stage decisions are made; s is the scenario of the happening of random events; p_s is probability of event ω_s, $\sum p_s = 1$; $Q(y, \omega_s)$ is system recourse at the second-stage under the occurrence of event ω_s; $\sum_{s=1}^{N} p_s Q(y, \omega_s)$ is expected value of the second-stage system penalties.

The existing TSP methods are effective in handling probabilistic uncertainties in the model's right-hand sides which are often related to resources availability; however they have difficulties in dealing with independent uncertainties of the model's left-hand sides and cost coefficients. Interval-parameter programming (IPP) is an alternative for handling uncertainties in the model's left-and/or right-hand sides as well as those that cannot be quantified as membership or distribution functions, since interval numbers are acceptable as its uncertain inputs. Let $x^{\pm}$ be a set of intervals with crisp lower bound (e.g., x^-) and upper bounds (i.e., x^+), but unknown distribution information. Let x be a set of closed and bounded interval numbers $x^{\pm}$ [35]:

$$x^{\pm} = [x^-, x^+] = \{t | x^- \leqslant t \leqslant x^+\} \tag{2}$$

Through introducing interval parameters into Model 1, the ITSP model can be formulated as follows:

$$\min \quad f^{\pm} = c^{\pm} x^{\pm} + \sum_{s=1}^{N} p_s Q(y^{\pm}, \omega_s^{\pm}) \tag{3a}$$

$$\text{subject to}: \quad a^{\pm} x^{\pm} \leqslant b^{\pm} \tag{3b}$$

$$T(\omega_s^{\pm})x^{\pm} + W(\omega_s^{\pm})y^{\pm} = h(\omega_s^{\pm}) \tag{3c}$$

$$x^{\pm} \geqslant 0, y(\omega_s^{\pm}) \geqslant 0 \tag{3d}$$

Fuzzy credibility constrained programming

Fuzzy credibility constrained programming (FCCP), which based on credibility conception, can be expressed as follows [36]:

$$\text{Min} \quad c_j x_j \tag{4a}$$

$$\text{Subject to}: \quad Cr\left\{\sum_{j=1}^{n} a_{ij} x_j \leqslant \tilde{b}_i, i = 1, 2, \ldots, \text{m}\right\} \geqslant \lambda_i \tag{4b}$$

$$x_j \geqslant 0, i = 1, \ldots, n \tag{4c}$$

where $x = (x_1, x_2, \ldots, x_n)$ is a vector of non-fuzzy decision variables; c_j are cost coefficients; a_{ij} are technical coefficients; $\tilde{b}_i$ are right-hand side coefficients; $Cr\{\cdot\}$ denotes the credibility of the event $\{\cdot\}$; λ is the confidence level.

Let ξ be a fuzzy variable with membership function μ, and let u and r be real numbers. Dubois and Prade proposed the following indices defined by possibility and necessity measures [36,37]:

$$\text{Pos}\{\xi \leqslant r\} = \sup_{u \leqslant r} \mu(u) \tag{5a}$$

$$\text{Nec}\{\xi \leqslant r\} = 1 - \text{Pos}\{\xi > r\} = 1 - \sup_{u > r} \mu \tag{5b}$$

The credibility measure Cr is the average of the possibility measure and the necessity measure:

$$\text{Cr}\{\xi \leqslant r\} = \frac{1}{2}(\text{Pos}\{\xi \leqslant r\} + \text{Nec}\{\xi \leqslant r\}) \tag{6}$$

Let the fuzzy variable ξ be fully determined by the triplet $(\underline{t}, t, \bar{t})$ of crisp numbers with $(\underline{t} < t < \bar{t})$, whose membership function is given by

$$\mu(r) = \begin{cases} (r - \underline{t})/(t - \underline{t}) & \text{if } \underline{t} \leqslant r \leqslant t, \\ (\bar{t} - r)/(\bar{t} - t) & \text{if } t \leqslant r \leqslant \bar{t}, \\ 0 & \text{otherwise}. \end{cases} \tag{7}$$

From the above definitions, the possibility, necessity, and credibility of $r \leqslant \xi$ are provided as follows:

$$\text{Pos}\{\xi \leqslant r\} = \begin{cases} 0 & \text{if } r \leqslant \underline{t} \\ \frac{r - \underline{t}}{t - \underline{t}} & \text{if } \underline{t} \leqslant r \leqslant t \\ 1 & \text{if } r \geqslant t \end{cases} \tag{8a}$$

$$\text{Nec}\{\xi \leqslant r\} = \begin{cases} 0 & \text{if } r \leqslant t \\ \frac{r - t}{\bar{t} - t} & \text{if } t \leqslant r \leqslant \bar{t} \\ 1 & \text{if } r \geqslant \bar{t} \end{cases} \tag{8b}$$

$$Cr(r \leqslant \xi) = \begin{cases} 0 & \text{if } r \leqslant \underline{t} \\ \frac{r - \bar{t}}{2(t - \bar{t})} & \text{if } \underline{t} \leqslant r \leqslant t \\ \frac{2t - \underline{t} - r}{2(t - \underline{t})} & \text{if } t \leqslant r \leqslant \bar{t} \\ 1 & \text{if } r \geqslant \bar{t} \end{cases} \tag{8c}$$

Let $\sum_{j=1}^{n} a_{ij} x_j$ be replaced by s_i. Thus, the constraint (4b) can be represented as:

$$Cr\left\{s_i \leqslant \tilde{b}_i, i = 1, \ldots, m\right\} \geqslant \lambda_i, \tag{9}$$

Normally, a significant credibility level should be greater than 0.5. Therefore, based on the definition of credibility, we have the following equation for each $1 \geqslant \mu_{\tilde{t}_i} \geqslant \lambda_i \geqslant 0.5$:

$$\frac{2b_i - \underline{b}_i - s_i}{2(b_i - \underline{b}_i)} \geqslant \lambda_i \tag{10}$$

where $\tilde{b}_i$ are right-hand side coefficients fully determined by the triplet $(\underline{b}_i, b_i, \bar{b}_i)$ of crisp numbers with $\underline{b}_i < b_i < \bar{b}_i$, whose membership function is μ.

Let $\sum_{j=1}^{n} a_{ij} x_j = s_i$ be the credibility constraints. The interval credibility levels, parameters and variables for such constraints can be formulated as:

$$Cr\{s_i \leqslant \tilde{b}_i, i = 1, \ldots, m\} \geqslant \lambda_i. \tag{11}$$

Therefore, based on the definition of credibility, we have the following expression for each $1 \geqslant \mu_{\tilde{t}_i} \geqslant \lambda_i \geqslant 0.5$:

$$\frac{2b_i - \underline{b}_i - s_i}{2(b_i - \underline{b}_i)} \geqslant \lambda_i \tag{12}$$

Thus, the FCCP can be transformed to an equivalent model as follows:

$$\text{Min} \quad \sum_{j=1}^{n} c_j x_j \tag{13a}$$

$$\text{Subject to :} \quad \sum_{j=1}^{n} a_{ij} x_j \leqslant b_i + (1 - 2\lambda_i)(b_i - \underline{b}_i) \tag{13b}$$

$$x_j \geqslant 0, \ \forall j \tag{13c}$$

Inexact stochastic-fuzzy chance-constrained programming

To tackle multi-type uncertainties, the ITSP and FCCP methods can be incorporated within a general optimization framework. Then an inexact stochastic-fuzzy chance-constrained programming model can be formulated as follows:

$$\text{Min} \quad f^{\pm} = \sum_{j=1}^{n} c_j^{\pm} x_j^{\pm} + \sum_{j=1}^{n}\sum_{h=1}^{v} p_{jh} d_j^{\pm} y_{jh}^{\pm} \tag{14a}$$

$$\text{subject to :} \quad \sum_{j=1}^{n} a_{ij}^{\pm} x_j^{\pm} \leqslant b_i + (1 - 2\lambda_i^{\pm})(b_i - \underline{b}_i) \tag{14b}$$

$$T(\omega_s^{\pm}) x_j^{\pm} + W(\omega_s^{\pm}) y_{jh}^{\pm} = h(\omega_s^{\pm}) \tag{14c}$$

$$x_j^{\pm} \geqslant 0, x_j^{\pm} \in X^{\pm}, \quad j = 1,2,\ldots,n_1 \tag{14d}$$

$$y_{jh}^{\pm} \geqslant 0, y_{jh}^{\pm} \in Y^{\pm}, \quad j = 1,2,\ldots,n_2; \quad h = 1,2,\ldots,v. \tag{14e}$$

Model (14) 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 [38]. The objective function value corresponding to f^- is desired first because the objective is to minimize net system costs. Based on the above solutions, the submodel for f^- can be formulated as follows:

$$\text{Min} \quad f^- = \sum_{j=1}^{k_1} c_j^- x_j^- + \sum_{j=k_1+1}^{n} c_j^- x_j^+ + \sum_{j=1}^{k_2}\sum_{s=1}^{v} p_s d_j^- y_{js}^- + \sum_{j=k_2+1}^{n}\sum_{s=1}^{v} p_s d_j^- y_{js}^+ \tag{15a}$$

$$\text{subject to :} \quad \sum_{j=1}^{k_1} \left|a_{ij}^{\pm}\right|^{+} sign(a_{ij}^{\pm}) x_j^- + \sum_{j=k_1+1}^{n} \left|a_{ij}^{\pm}\right|^{-} sign(a_{ij}^{\pm}) x_j^+ \leqslant b_i + (1 - 2\lambda_i^{+})(b_i - \underline{b}_i) \tag{15b}$$

$$\sum_{j=1}^{k_1} \left|a_{rj}^{\pm}\right|^{+} \text{sign}\left(a_{rj}^{\pm}\right) x_j^- + \sum_{j=k_1+1}^{n_1} \left|a_{rj}^{\pm}\right|^{-} \text{sign}(a_{rj}^{\pm}) x_j^+ \leqslant b_r^-, \forall r \tag{15c}$$

$$\sum_{j=1}^{k_1} T(\omega_s^-) x_j^- + \sum_{j=k_1+1}^{n} T(\omega_s^-) x_j^+ + \sum_{j=1}^{k_2} W(\omega_s^-) y_{js}^- + \sum_{j=k_2+1}^{n} W(\omega_s^-) y_{js}^+ = h(\omega_s^-) \forall s \tag{15d}$$

$$\sum_{s=1}^{v} p_s = 1 \tag{15e}$$

$$x_j^- \geqslant 0, \quad j = 1,2,\ldots,k_1 \tag{15f}$$

$$x_j^+ \geqslant 0, \quad j = k_1+1, k_1+2,\ldots,n \tag{15g}$$

$$y_{js}^- \geqslant 0, \quad \forall s; j = 1,2,\ldots,k_2 \tag{15h}$$

$$y_{js}^+ \geqslant 0, \quad \forall s; \quad j = k_2+1, k_2+2,\ldots,n \tag{15i}$$

where $x_j^{\pm}$, $j = 1, 2, \ldots, k_1$, are interval variables with positive coefficients in the objective function; $x_j^{\pm}$, $j = k_1 + 1, k_1 + 2, \ldots, n$ are interval variables with negative coefficients; $y_{jh}^{\pm}$, $j = 1, 2, \ldots, k_2$ and $h = 1, 2, \ldots, v$, are random variables with positive coefficients in the objective function; $y_{jh}^{\pm}$, $j = k_2 + 1, k_2 + 2, \ldots, n$ and $h = 1, 2, \ldots, v$, are random variables with negative coefficients [28,34,35]. Solutions of $x_{j\,opt}^-$ ($j = 1, 2, \ldots, k_1$), $x_{j\,opt}^+$ ($j = k_1 + 1, k_1 + 2, \ldots, n$), $y_{js\,opt}^-$ ($j = 1, 2, \ldots, k_2$), and $y_{js\,opt}^+$ ($j = k_2 + 1, k_2 + 2, \ldots, n$) can be obtained through submodel (15). Based on the above solutions, the second submodel for f^+ can be formulated as follows:

$$\text{Min} \quad f^+ = \sum_{j=1}^{k_1} c_j^+ x_j^+ + \sum_{j=k_1+1}^{n} c_j^+ x_j^- + \sum_{j=1}^{k_2}\sum_{s=1}^{v} p_s d_j^+ y_{js}^+ + \sum_{j=k_2+1}^{n}\sum_{s=1}^{v} p_s d_j^+ y_{js}^- \tag{16a}$$

$$\text{subject to :} \quad \sum_{j=1}^{k_1} \left|a_{ij}^{\pm}\right|^{-} \text{sign}(a_{ij}^{\pm}) x_j^+ + \sum_{j=k_1+1}^{n} \left|a_{ij}^{\pm}\right|^{+} \text{sign}(a_{ij}^{\pm}) x_j^- \leqslant b_i + (1 - 2\lambda_i^{-})(b_i - \underline{b}_i) \tag{16b}$$

$$\sum_{j=1}^{k_1} \left|a_{rj}^{\pm}\right|^{-} \text{sign}(a_{rj}^{\pm}) x_j^+ + \sum_{j=k_1+1}^{n_1} \left|a_{rj}^{-}\right|^{+} \text{sign}(a_{rj}^{\pm}) x_j^- \leqslant b_r^+, \forall r \tag{16c}$$

$$\sum_{j=1}^{k_1} T(\omega_s^+) x_j^+ + \sum_{j=k_1+1}^{n} T(\omega_s^+) x_j^- + \sum_{j=1}^{k_2} W(\omega_s^+) y_{js}^+ + \sum_{j=k_2+1}^{n} W(\omega_s^+) y_{js}^- = h(\omega_s^+) \forall s \tag{16d}$$

$$\sum_{s=1}^{v} p_s = 1 \tag{16e}$$

$$x_j^+ \geqslant x_{jopt}^- \geqslant 0, \ j = 1,2,\ldots,k_1 \tag{16f}$$

$$x_{j\,opt}^+ \geqslant x_j^- \geqslant 0, \ j = k_1+1, k_1+2,\ldots,n \tag{16g}$$

$$y_{js}^+ \geqslant y_{js\,opt}^- \geqslant 0, \forall s; \ j = 1,2,\ldots,k_2 \tag{16h}$$

$$y_{js\,opt}^+ \geqslant y_{js}^- \geqslant 0, \forall s; \ j = k_2+1, k_2+2,\ldots,n \tag{16i}$$

Solutions of $x_{j\,opt}^-$ ($j = 1, 2, \ldots, k_1$), $x_{j\,opt}^+$ ($j = k_1 + 1, k_1 + 2, \ldots, n$), $y_{js\,opt}^+$ ($j = 1, 2, \ldots, k_2$), and $y_{js\,opt}^-$ ($j = k_2 + 1, k_2 + 2, \ldots, n$) can be obtained through submodel (16). Through integrating solutions of submodels (15) and (16), interval solution for model (14) can be obtained as $f_{opt}^{\pm} = [f_{opt}^-, f_{opt}^+]$, $x_{j\,opt}^{\pm} = [x_{j\,opt}^-, x_{j\,opt}^+]$, and $y_{js\,opt}^{\pm} = [y_{js\,opt}^-, y_{js\,opt}^+]$.

Case study

Overview of the study system

The electric power system in this study is a micro-grid consisted of coal-fired generation, gas-fired generation, wind power and photovoltaic power generation. These conventional and renewable recourses are served for the regional electric demand. Besides, coal-fired power has a residual capacity of 2.5 GW, natural gas-fired power has a residual capacity of 1.5 GW, wind power and photovoltaic power generations have installed capacity of 0.95 and 1.15 GW. It supposes that the shortage of electricity would be satisfied by electricity purchased from the main grid, while that the electric power generated in micro-grid is self-consumed and not allowed to be sold to main grid. In order to encourage efficient forecasting and dispatch, there are penalties for deviations between the real time delivery and pre-designed schedules. From the aspect of environment protection, regional pollution emission control policy is considered in operation management. Extra pollutant treatment cost would be necessary to meet environmental demand.

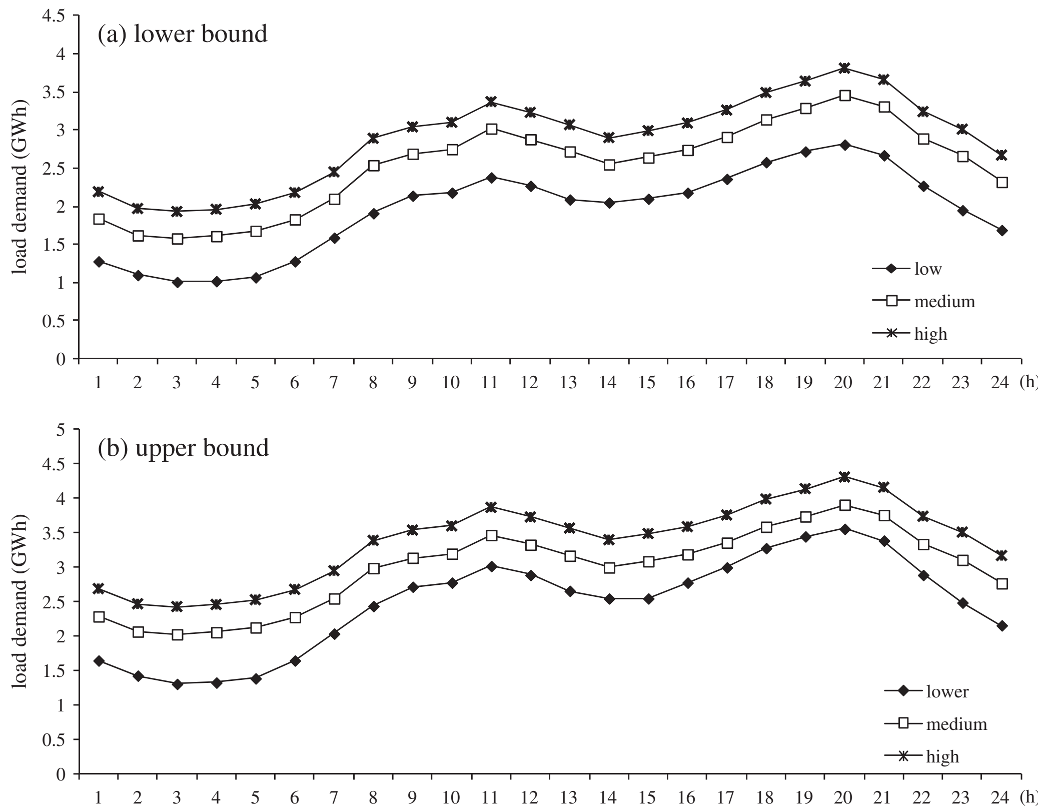

Fig. 2. Different load demand level for 24 h.

The decision maker can formulate the problem as minimizing the expected operation cost of regional power grid for day ahead and real time schedule. Moreover, decision makers always seek to control the emissions of environmental pollutants, and greenhouse gas (GHG) in order to meet the regional environmental requirement. According to the load demand and renewable energy generation forecasting, day-ahead generation is pre-designed. However, if the pre-designed generation plan could not satisfy the real-time demand, penalty for forecasting deviation would cause higher operation cost. In general, the study system is related to cost-effective generation scheduling optimal program considering distributed energy generation. Furthermore, a variety of uncertainties of operation cost, emissions of GHG and pollutants, environmental limitation and energy supply/demand are involved in this system.

The uncertainties of wind and photovoltaic power are formulated as probabilistic-based chance constrained programming. The regional power demand is expressed as three different scenarios (low, medium and high) by interval numbers with various probabilities (0.25, 0.60 and 0.15), which are given in Fig. 2. The price of sources (coal and natural gas) and the purchase price from the main grid are also handled by interval numbers. The operation cost for pre-designed and excess generation and pollutant treatment cost are described in Table 1. The representative costs and technical data are investigated based on governmental reports and other related literature [39-41]. In addition, here we suppose that a real time and dynamic amount control strategy is implemented on the emission of SO_2, NO_X and PM. While CO_2 emission is monitor by daily total amount control strategy.

ITSFCCP model for regional power electric system planning

The objective of the proposed model is to obtain a preferred plan for various energy activities by minimizing the total cost, which is related to energy resource supply, energy conversion, capacity expansion and environmental protection. The model constraints involve mass balance, emission, and technical restrictions. The regional power electric system planning problem can then be formulated as follows:

$$\text{Minimize } f^{\pm} = \sum_{i=1}^{4}\sum_{t=1}^{24} PR_{it}^{\pm} \cdot Z_{it}^{\pm} + \sum_{k=1}^{4}\sum_{t=1}^{24} PV_{kt}^{\pm} \cdot W_{kt}^{\pm} + \sum_{k=1}^{4}\sum_{t=1}^{24}\sum_{h=1}^{3} p_{th} \cdot PP_{kt}^{\pm} \cdot Q_{kth}^{\pm} + \sum_{t=1}^{24} PPE_{t}^{\pm} \cdot IE_{t}^{\pm} + \sum_{k=1}^{4}\sum_{t=1}^{24}\sum_{r=1}^{3}\sum_{h=1}^{3} (W_{kt}^{\pm} + p_{th} \cdot Q_{kth}^{\pm}) \cdot PD_{krt}^{\pm} \cdot CT_{krt}^{\pm} \quad (17a)$$

Table 1
Value of relative parameters.

	$k = 1$	$k = 2$	$k = 3$	$k = 4$
$PV^{\pm}(10^3\$/\text{GW h})$	[4.89, 5.78]	[4.55, 5.25]	[8.21, 8.97]	[6.57, 7.29]
$PP^{\pm}(10^3\$/\text{GW h})$	[6.87, 8.53]	[6.2, 7.4]	[10.18, 11.22]	[8.13, 9.62]
$SOT_{kt}^{\pm}$(tonne/GW h)	[6, 7.25]	[0.05, 0.07]	–	–
$NOT_{kt}^{\pm}$(tonne/GW h)	[3.15, 3.42]	[0.6, 0.75]	–	–
$POT_{kt}^{\pm}$(tonne/GW h)	[0.95, 1.16]	[0.05, 0.76]	–	–
$COT_{kt}^{\pm}$(kilotones/GW h)	[0.93, 0.98]	[0.61, 0.68]	–	–

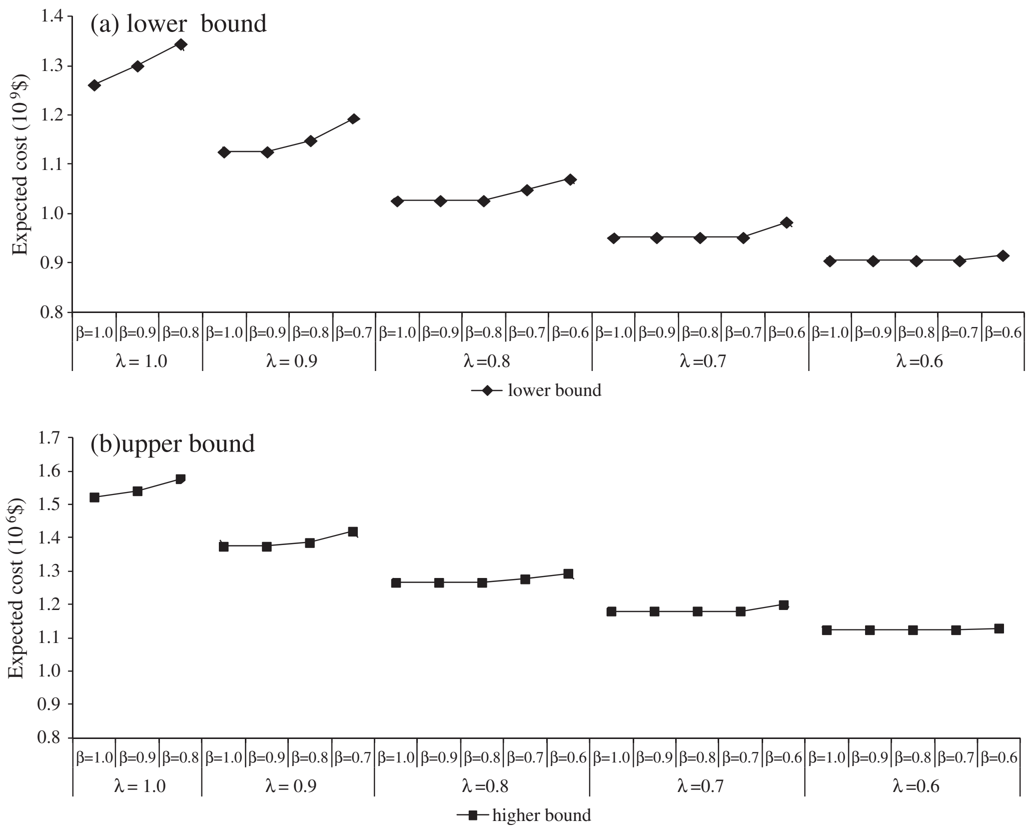

Fig. 3. Expected cost of electric power system under different λ and β.

Table 2
Pre-designed power generation strategies under different λ and β on typical hours (GW h).

	k = 1	k = 2	k = 3	k = 4	k = 1	k = 2	k = 3	k = 4	k = 1	k = 2	k = 3	k = 4
λ = 1.0	β = 0				β = 0.90				β = 0.80			
t = 4	0.443	0.180	0	0.047	0.350	0.366	0	0.047	0.200	0.516	0	0.047
t = 8	0.676	0.180	0.174	0.105	0.350	0.832	0.174	0.105	0.240	0.942	0.174	0.105
t = 12	0.547	0.200	0.294	0.275	0.350	0.593	0.294	0.275	0.260	0.683	0.294	0.275
t = 16	0.443	0.180	0.112	0.500	0.350	0.366	0.112	0.500	0.260	0.456	0.112	0.500
t = 20	1.034	0.180	0	0.381	0.619	1.010	0	0.381	0.374	1.500	0	0.381
t = 24	0.571	0.180	0	0.275	0.350	0.621	0	0.275	0.220	0.751	0	0.275
λ = 0.8	β = 0				β = 0.80				β = 0.60			
t = 4	0.420	0.180	0	0.070	0.420	0.180	0	0.070	0.200	0.470	0	0.070
t = 8	0.520	0.180	0.278	0.156	0.520	0.180	0.278	0.156	0.240	0.631	0.278	0.156
t = 12	0.260	0.200	0.470	0.409	0.260	0.200	0.470	0.409	0.260	0.200	0.470	0.409
t = 16	0.301	0.180	0.179	0.575	0.301	0.180	0.179	0.575	0.260	0.180	0.179	0.575
t = 20	0.848	0.180	0	0.568	0.848	0.180	0	0.568	0.260	1.265	0	0.568
t = 24	0.436	0.180	0	0.409	0.436	0.180	0	0.409	0.220	0.483	0	0.409
λ = 0.6	β = 0				β = 0.80				β = 0.60			
t = 4	0.397	0.180	0	0.093	0.397	0.180	0	0.093	0.397	0.180	0	0.093
t = 8	0.365	0.180	0.383	0.207	0.365	0.180	0.383	0.207	0.365	0.180	0.383	0.207
t = 12	0.260	0.200	0.442	0.543	0.260	0.200	0.442	0.543	0.260	0.200	0.442	0.543
t = 16	0.260	0.180	0.246	0.575	0.260	0.180	0.246	0.575	0.260	0.180	0.246	0.575
t = 20	0.840	0.180	0	0.575	0.840	0.180	0	0.575	0.425	1.010	0	0.575
t = 24	0.302	0.180	0	0.543	0.302	0.180	0	0.543	0.254	0.180	0	0.543

subject to:

(1) Constraint for coal balance

$$\left[W_{1t}^{\pm} + Q_{1th}^{\pm}\right] \cdot FE_{1t}^{\pm} \leqslant Z_{1t}^{\pm}, \forall t, h \tag{17b}$$

(2) Constraint for natural gas balance

$$\left[W_{2t}^{\pm} + Q_{2th}^{\pm}\right] \cdot FE_{2t}^{\pm} \leqslant Z_{2t}^{\pm}, \forall t, h \tag{17c}$$

(3) Constraint for solar power

$$Cr\left\{\left[W_{3t}^{\pm} + Q_{3th}^{\pm}\right] \cdot FE_{3t}^{\pm} \leqslant Z_{3t}^{\pm}\right\} \geqslant \lambda^{\pm}, \forall t, h \tag{17d}$$

(4) Constraint for wind power

$$Cr\left\{\left[W_{4t}^{\pm} + Q_{4th}^{\pm}\right] \cdot FE_{4t}^{\pm} \leqslant Z_{4t}^{\pm}\right\} \geqslant \lambda^{\pm}, \forall t, h \tag{17e}$$

(6) Constraint for electricity demand

$$\sum_{k=1}^{4} W_{kt}^{\pm} + \sum_{k=1}^{4} Q_{kth}^{\pm} + IE_{t}^{\pm} \geqslant D_{th}, \forall t, h \tag{17f}$$

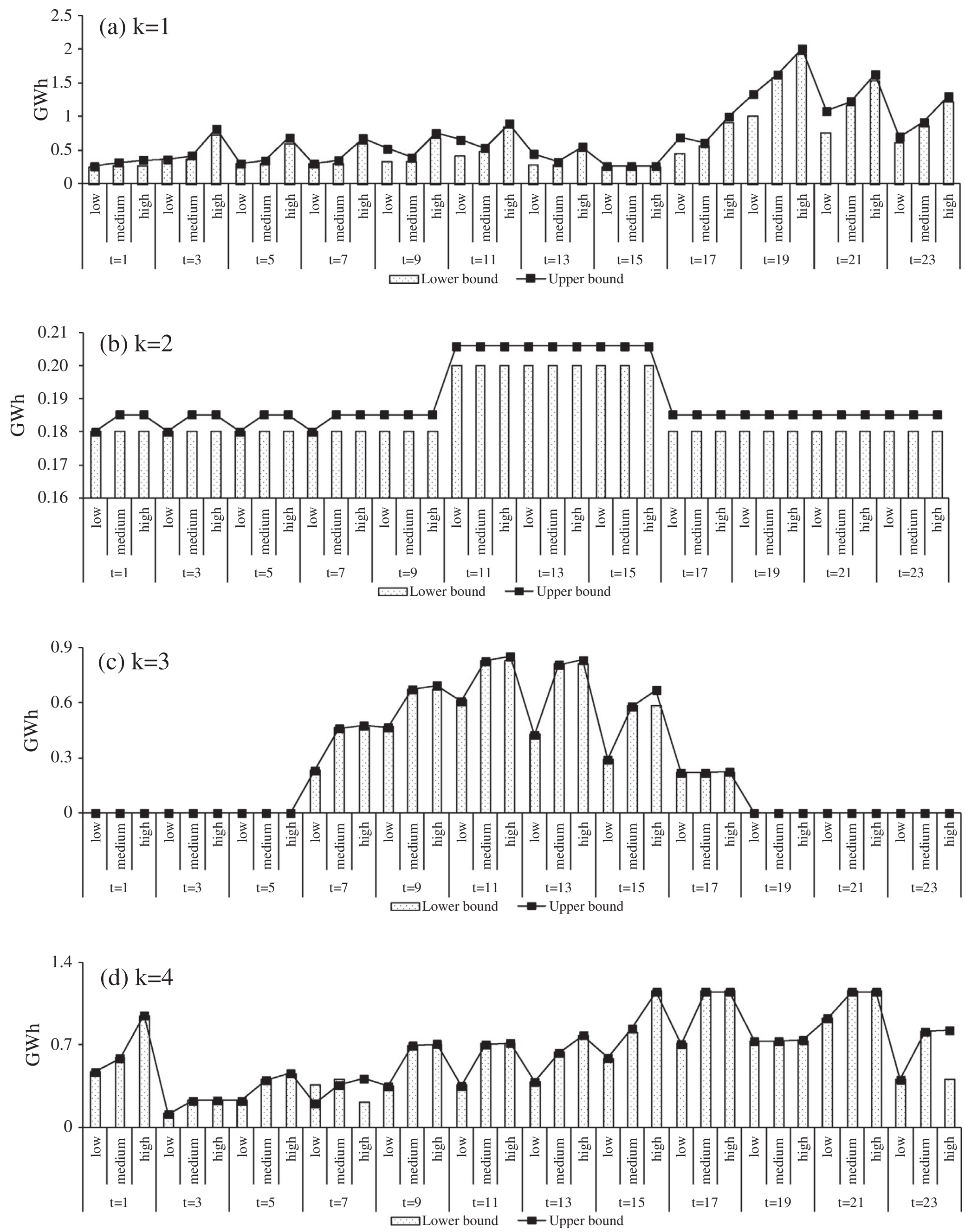

Fig. 4. Optimal dispatch of electric system with $\lambda = 0.8$ and $\beta = 0$.

(7) Constraint for environmental protection

$$\sum_{k=1}^{4}\left(W_{kt}^{\pm}+Q_{kth}^{\pm}\right)\cdot SOT_{kt}^{\pm}\cdot\left(1-\eta_{kt}^{\pm}\right)\leqslant ES_{t}^{\pm},\forall t \tag{17g}$$

$$\sum_{k=1}^{4}\left(W_{kt}^{\pm}+Q_{kth}^{\pm}\right)\cdot NOT_{kt}^{\pm}\cdot\left(1-\eta_{kt}^{\pm}\right)\leqslant EN_{t}^{\pm},\forall t \tag{17h}$$

$$\sum_{k=1}^{4}\left(W_{kt}^{\pm}+Q_{kth}^{\pm}\right)\cdot POT_{kt}^{\pm}\cdot\left(1-\eta_{kt}^{\pm}\right)\leqslant EP_{t}^{\pm},\forall t \tag{17i}$$

$$\sum_{t=1}^{24}\sum_{k=1}^{4}\left(W_{kt}^{\pm}+Q_{kth}^{\pm}\right)\cdot COT_{kt}^{\pm}\leqslant EC_{t}^{\pm},\forall t \tag{17j}$$

(8) Constraint for environmental protection

$$W_{kt}^{\pm}+Q_{kth}^{\pm}\leqslant RC_{k}\cdot ST_{kt}^{\pm}\cdot\beta_{k}^{\pm},\forall k,t \tag{17k}$$

$$Q_{kth}^{\pm}\leqslant W_{kt}^{\pm}\leqslant W_{kt\,\max}^{\pm},\forall k,t \tag{17l}$$

(9) Constraint for technical and non-negative

$$Z_{it}^{\pm}\geqslant 0,\forall i,t \tag{17m}$$

$$W_{kt}^{\pm}\geqslant 0,\forall k,t \tag{17n}$$

The detailed nomenclatures for the variables and parameters are provided in Appendix A.

Results analysis and discussion

Through solving the proposed model, detailed generation scheduling strategies are obtained under different confidence levels (λ = 1.0, 0.9, 0.8, 0.7 and 0.6) and CO_2 emission goal (0%, 10%, 20%, 30% and 40% emission reduction). According to interval optimal theory, the value of objective function is also expressed as interval number. The lower bound and upper bound of expected

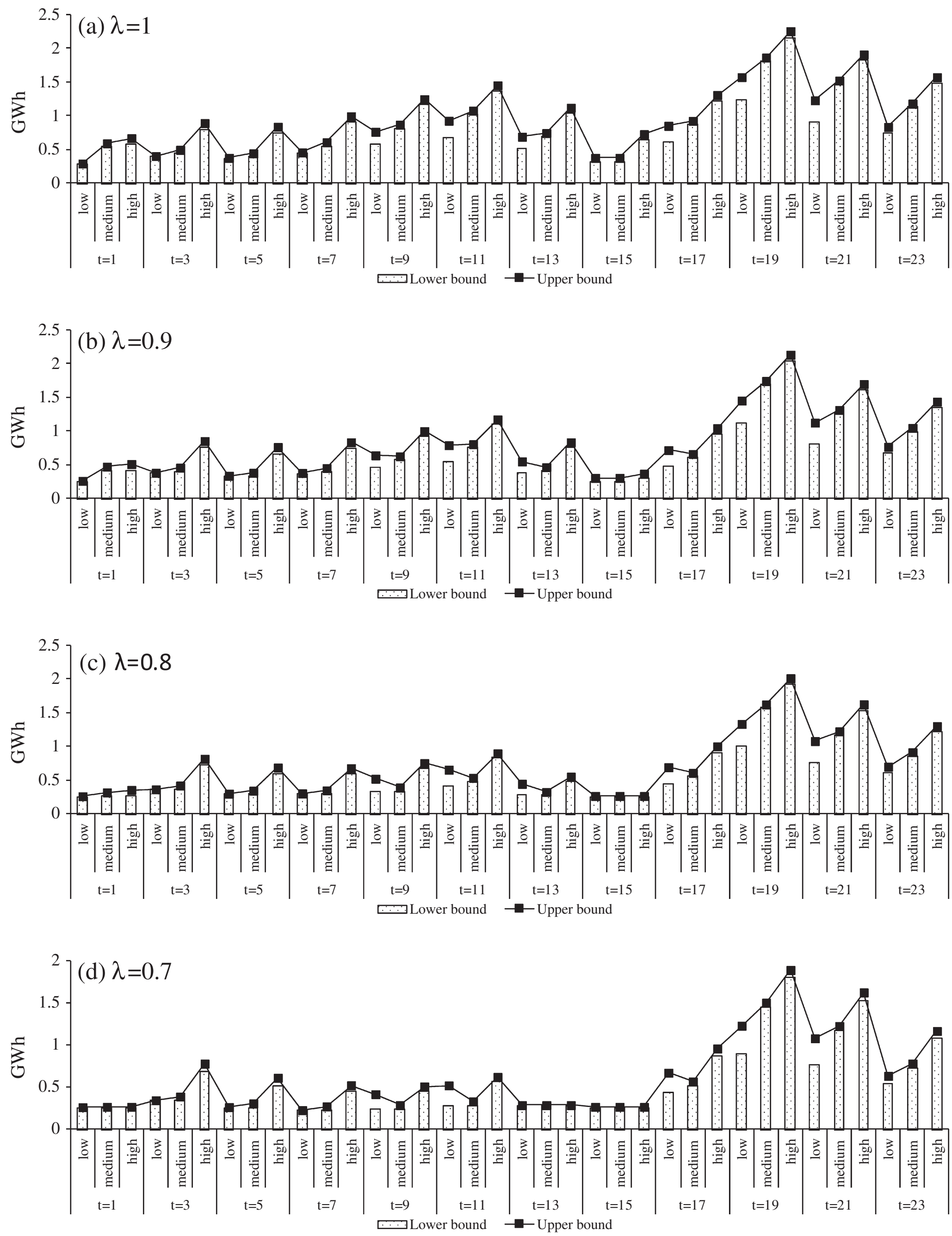

Fig. 5. Output of coal-fired generation with different λ values and $\beta = 0$.

cost under different scenarios are illustrated in Fig. 3. It indicated that a higher confidence level and stricter emission goal, a higher the expected cost of electric system. For example, under confidence level $\lambda = 1.0$, the expected cost of electric system would be \$ $[1.2628,\ 1.5226] \times 10^9$, \$ $[1.3003,\ 1.5412] \times 10^9$, and \$ $[1.3447,\ 1.5775] \times 10^9$ with 0%, 10% and 20% CO_2 emission goal, respectively. In addition, under the scenarios of 20% CO_2-mitigation, the expected cost would be $[1.1260,\ 1.3747]$, $[1.0271,\ 1.2663]$, $[0.9524,\ 1.1802]$ and $[0.9055,\ 1.1241] \times 10^9$ \$ under $\lambda = 0.9$, 0.8, 0.7, and 0.6, respectively. Moreover, when the confidence level is low, the change of expected cost under different emission goals would be small. As shown in Fig. 3, as the confidence level decrease, the expected system cost is lower. At the meanwhile, the changes of emission reduction goal impact the cost less. Especially, when the value of confidence level λ were fixed at 0.7 and 0.6, the values of objective function are the same for 0%, 10%, 20% and 30% emission reduction goals.

Table 2 presents the pre-designed power generation strategies of various technologies with different λ and β. Given the forecasted renewable generation under a certain confidence level, the coal-fired generation would decrease with the stricter environmental policy, and gas-fired generation would increase. For instance, when λ set as 1.0, with the 10% emission reduction goal, the pre-designed coal-fired power generation would be 0.350, 0.350 and 0.619 GW h at 4:00, 12:00 and 20:00, respectively; for the 20% emission reduction goal, it would be 0.200, 0.2600 and 0.374 GW h accordingly. By contrast, in the former situation, the gas-fired generation would be 0.366, 0.593 and 1.010 GW h, respectively; and it would increase as

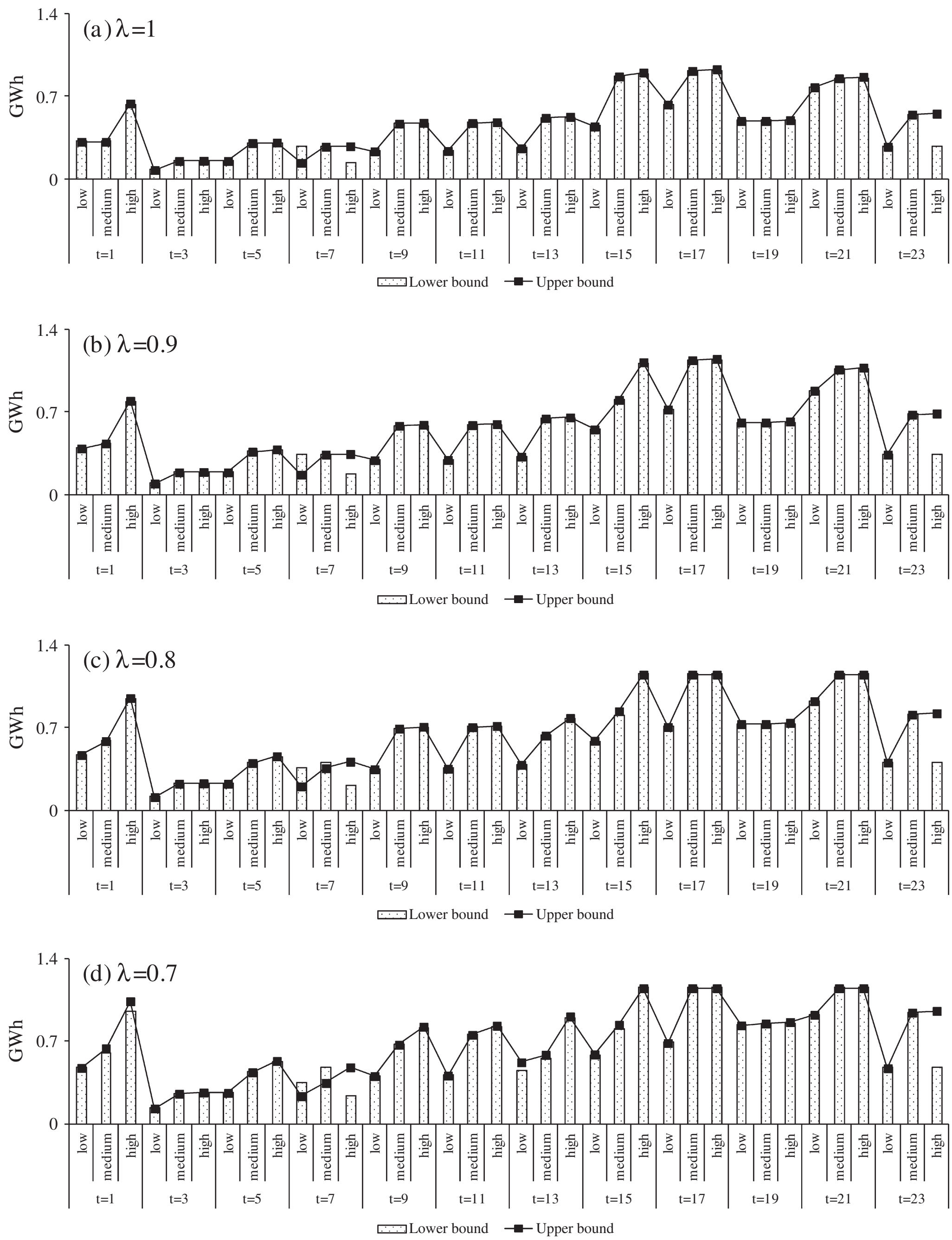

Fig. 6. Output of wind power generation with different λ values and $\beta = 0$.

0.516, 0.683 and 1.500 for the latter emission goal. In the other hand, the lower confidence level indicates higher forecasted value of renewable energy generation, thus the pre-designed traditional generation would be less, which lower the system security when emergency occurs. For example, with the same 20% emission reduction goal, the total pre-designed coal-fired generation and gas-fired generation at 4:00 and 12:00 would be 0.577 and 0.440 GW h under λ set as 0.6; and under λ set as 0.8 the corresponding pre-designed generation would be 0.600 and 0.460 GW h, respectively.

Fig. 4 presents the performance of various generation technologies with confidence level at 0.8 and no emission reduction goal. In general, the pre-regulated electricity generated by coal-fired power, gas-fired power, photovoltaic and wind power conversion technologies would increase with the electricity demand level increasing. For example, at 19:00, the coal-fired generation would be [1.001, 1.334], [1.579, 1.624] and [1.929, 2.013] GW h for low, medium and high load demand level, respectively. At 5:00, the gas-fired generation would be 0.18, [0.18, 0.185] and [0.18, 0.185] GW h for low, medium and high load demand level. Due to the low cost of power generation and resources supply, the electricity demand would be firstly satisfied by coal-fired power, especially during periods of demand peak. The power curves of renewable energy are almost determined by the weather condition, and the photovoltaic power generation would fluctuate over the planning horizon. The night load peak is mainly met by coal-fired generation and wind power. For example, in the high demand scenario, at 21:00, the power of coal-fired generation, gas-fired

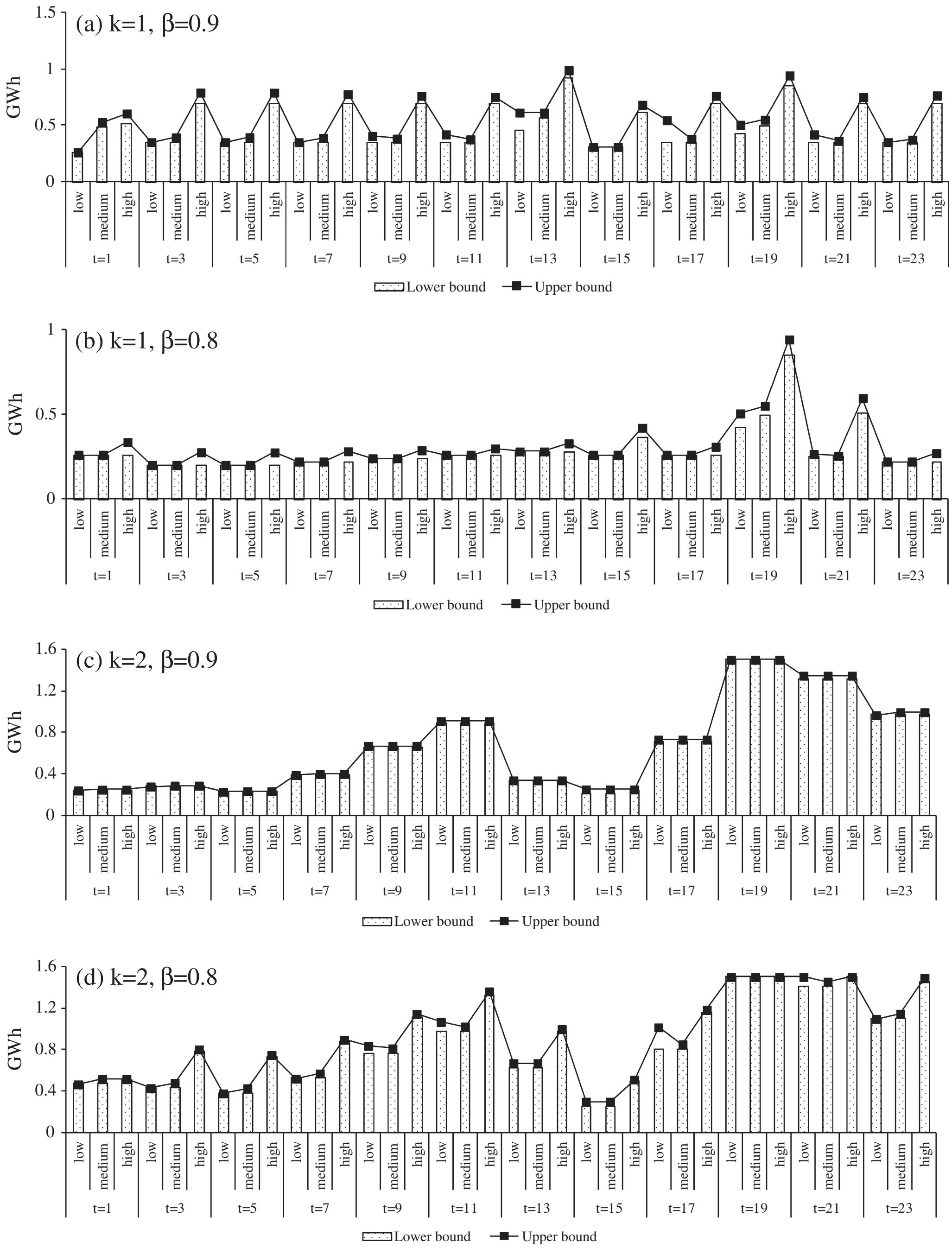

Fig. 7. Schedule of traditional generation with λ = 1.0 for different emission reduction goals.

generation, photovoltaic and wind power generation would be [1.530, 1.625], [0.180, 0.185], 0 and 1.15 GW h, respectively; and [0.765, 1.080], [0.180, 0.185], 0 and 0.925 GW h under the low demand level, respectively.

The performances of coal-fired generation with different confidence levels without emission reduction are compared in Fig. 5. The maximum power generation of coal-fired power would be during 19:00–21:00, which was consistent with the night peak load demand. During the period of 1:00–3:00 and 13:00–15:00, electricity generation of coal-fired power would be relatively lower. As the increasing confidence level, power output of coal-fired generator would increase gradually. For example, at 13:00, in order to satisfy the medium load demand, the coal-fired power generation would be [0.280, 0.285], [0.280, 0.324], [0.421, 0.465] and [0.698, 0.742] GW h under the confidence level λ set as 0.7, 0.8, 0.9 and 1.0, respectively. In addition, for the same time period, in high load demand scenario, the output power of coal-fired generator would be [0.280, 0.285], [0.493, 0.550], [0.770, 0.834] and [1.048, 1.119] GW h, accordingly. It indicated that without CO_2 mitigation, as the confidence level increasing, the renewable energy would be insufficient and the output of photovoltaic and wind power conversion technologies would decrease, and the coal-fired power generation would be the most significant part of electricity supply.

Compared with the traditional generation technology, the performances of renewable energy generation are different under the scenarios of 0% CO_2 mitigation. Fig. 6 shows the wind power generation without CO_2 emission reduction under different confidence levels. From 15:00 to 21:00, the wind power generation

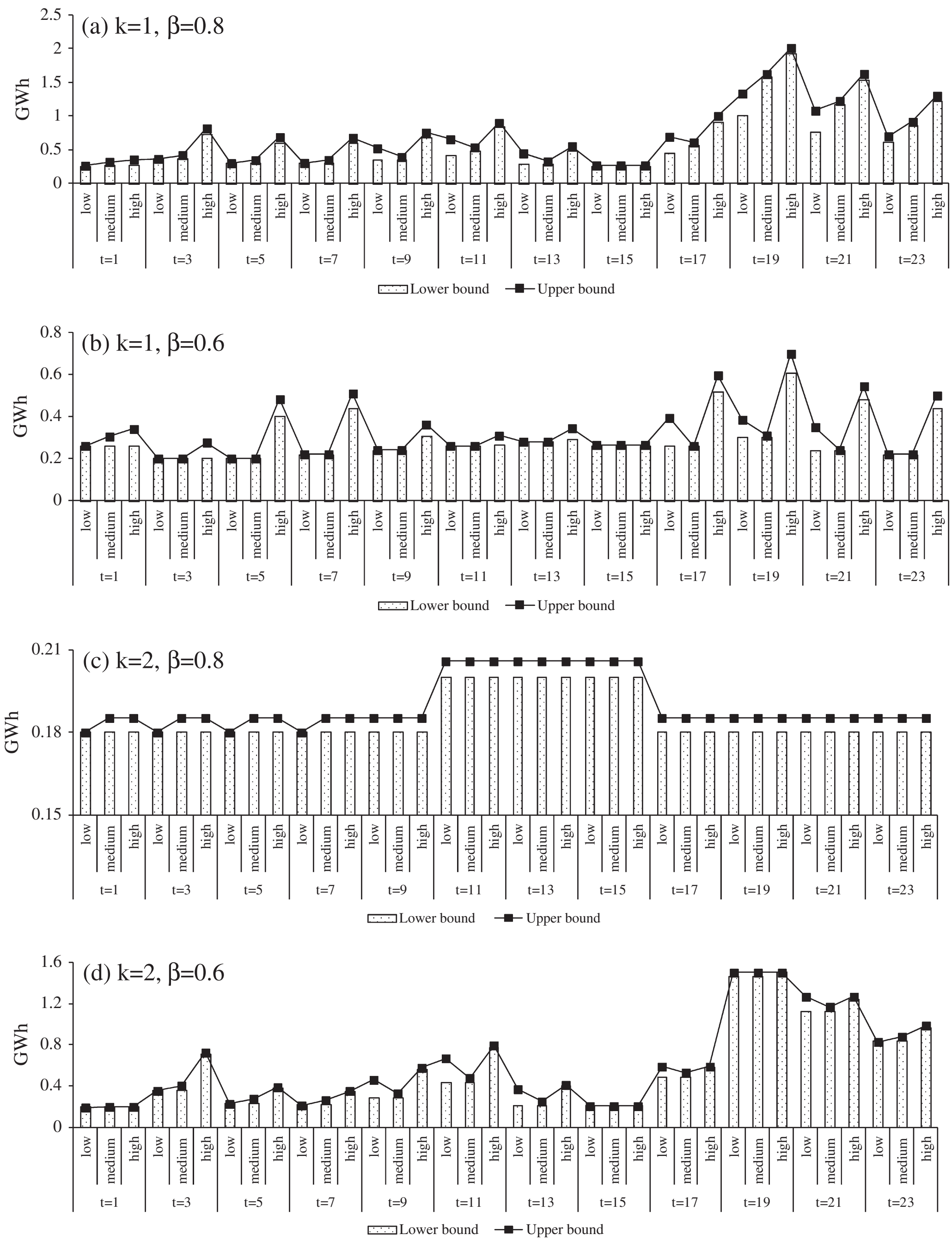

Fig. 8. Schedule of traditional generation with $\lambda = 0.8$ for different emission reduction goals.

would be in a high loading operation condition. For example, under the high demand level, the wind power generation would be [0.378, 0.383] and [0.611, 0.620] GW h in 5:00 and 19:00, when the confidence level is fixed at 0.9. In addition, as the confidence level increasing, the wind energy resources would be decreased, and the output of the wind power would decrease. For example, under the high load demand at 15:00, wind power generation would be 1.15, 1.15, [1.105, 1.122] and [0.888, 0.901] GW h with the confidence level fixed at 0.7, 0.8, 0.9 and 1.0, respectively. For the low load demand scenario, the wind power generation would be [0.575, 0.590], [0.575, 0.590], 0.553 and 0.444 GW h, with the confidence level fixed at 0.7, 0.8, 0.9 and 1.0, respectively. It also indicated that due to the security consideration and risk-averse, the wind power generation would be lower, and that would reduce the risk of unsteady of wind power supply.

Figs. 7 and 8 present the impact of emission reduction goal on the scheduling of traditional power generation technologies. With GHG-emission reduction increasing, strict environmental policies for GHG mitigation management would be adopted. Thus, electricity generated from coal-fired power conversion technologies would significantly decrease. Under the highest confidence level ($\lambda = 1$), the performance of coal-fired generator with $\beta = 0.9$ is much lower than that under $\beta = 0.8$ during daytime. At 9:00, under $\lambda = 1$and $\beta = 0.9$, the power output of coal-fired generator would be [0.350, 0.405], [0.350, 0.381], [0.700, 0.761] GW h for low, medium and high demand level, respectively. For the same situation, under $\lambda = 1$and $\beta = 0.8$, the power output of coal-fired generator would be 0.240, 0.240, [0.240, 0.287] GW h, respectively. While the power generated from gas-fired generator has obviously increased when emission reduction goal going up. For instance, at 11:00, under

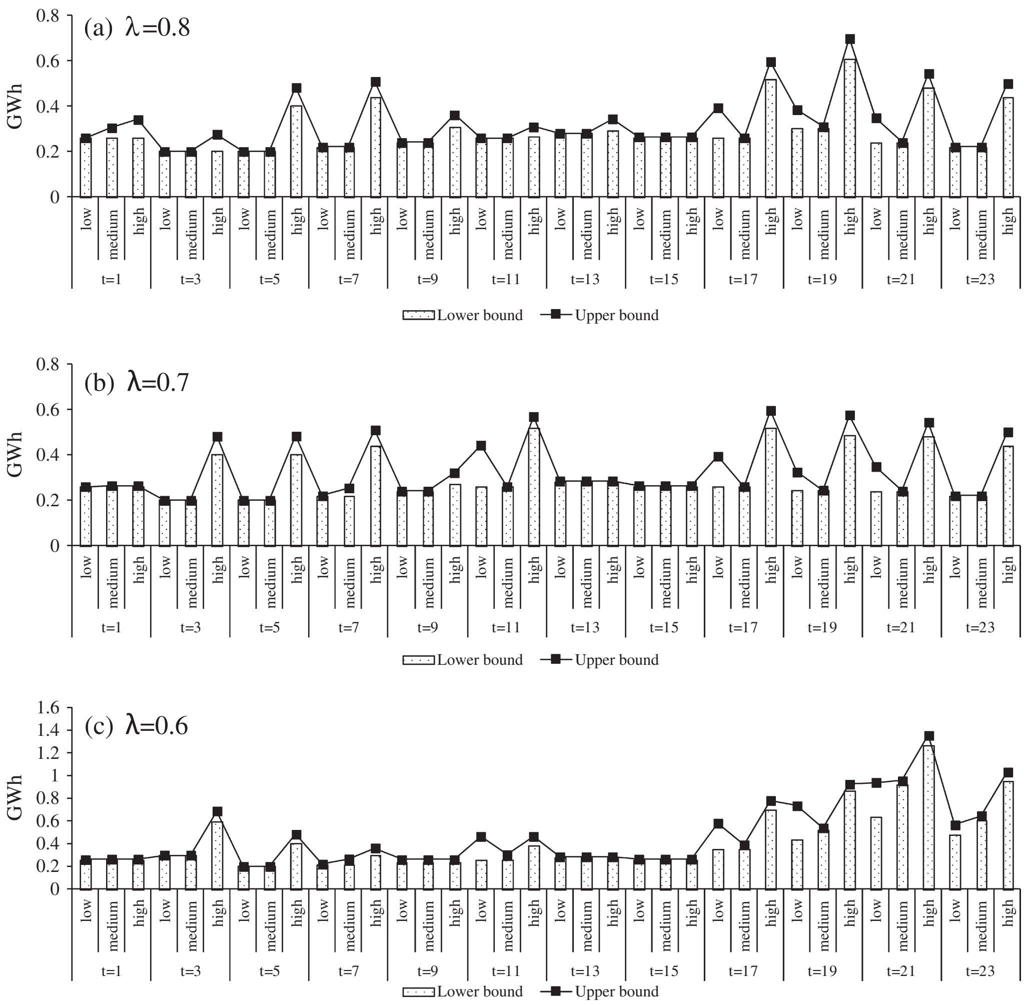

Fig. 9. Output of coal-fired generation with 40% emission reduction goal under different confidence level.

$\lambda = 1$ and $\beta = 0.9$, the power output of gas-fired generator would be [0.881, 0.907] GM h for all demand level; and when $\lambda = 1$and $\beta = 0.8$, it would increase to [0.971, 1.065], [0.971, 1.021] and [1.321, 1.360] GM h for low, medium and high power demand, respectively. Compared with the power generation of the two energy conversation technologies under CO_2 mitigation condition in Figs. 7 and 8, as the confidence level and CO_2-mitgation increasing, the regional electricity system would face double pressures from environmental protection and insufficient renewable energy. Natural gas power would be more popular than coal-fired power in considering the case of GHG-emission reduction. This is because the totaling amount of GHG emissions would be confined with a certain level during the planning periods, while coal-fired power conversion technology corresponds to a higher GHG-emission rate, compared with natural gas-fired conversion technologies.

If the decision maker is risk-averse, a large λ value should be employed. On the contrary, if the planner is a risk-taker, a small λ value should be utilized. Figs. 9 and 10 evaluate the performance of traditional generation and renewable resources generation under different confidence levels. As shown in Fig. 9, the output power of coal-fired generation is increasing with the confidence level increases, especially during the daytime. For example, at 7:00 with λ set as 0.8, the output power of coal-fired generator would be 0.22, 0.22 and [0.44, 0.509] GW h for low medium and high level, respectively. When λ set as 0.7, it would be 0.22, [0.22, 0.2543] and [0.44, 0.510] GW h, for λ set as 0.6, it would be 0.22, [0.22, 0.265] and [0.297, 0.364] respectively. As to photovoltaic generation, illustrated in Fig. 10, its maximum output would be at 13:00. When the value of λ is 0.8, its output would be 0.4246, 0.8064, [0.8064, 0.8321] GW h for low, medium and high demand level. When λ is fixed as 0.7, the output would be 0.4463, 0.8925 and [0.8926, 0.9684] GW h correspondingly. For the value of λ is fixed at 0.6, it would be 0.3830, 0.7660 and [0.7660, 0.8399] GW h. It indicates that for 40% emission reduction goals, when confidence level set as 0.7, the output of both coal-fired and photovoltaic generation is higher. In addition, as λ increasing, the decision-maker possesses rather conservative review to the development of renewable energy. Since the emission reduction implementation is strengthened, the electricity system have to supply more spinning reserve to reduce the relative risk of unsteady of wind and photovoltaic power, which also increases the system environmental pressure and brings extra burden.

The micro-grid system management and planning problem can be solved under different confidence levels and pollutants mitigation intensity, and further sensitivity analysis could be undertaken by considering the interactions among various uncertainties. Compared with Table 2, and Figs. 5, 6 and 8, the detailed generation scheduling strategies with different scenarios are associated with lower- and upper-bound levels of different power supply activities; they are optimistic choices and could result in a low system cost and, at the same time, lower CO_2 discharge amounts (and thus a

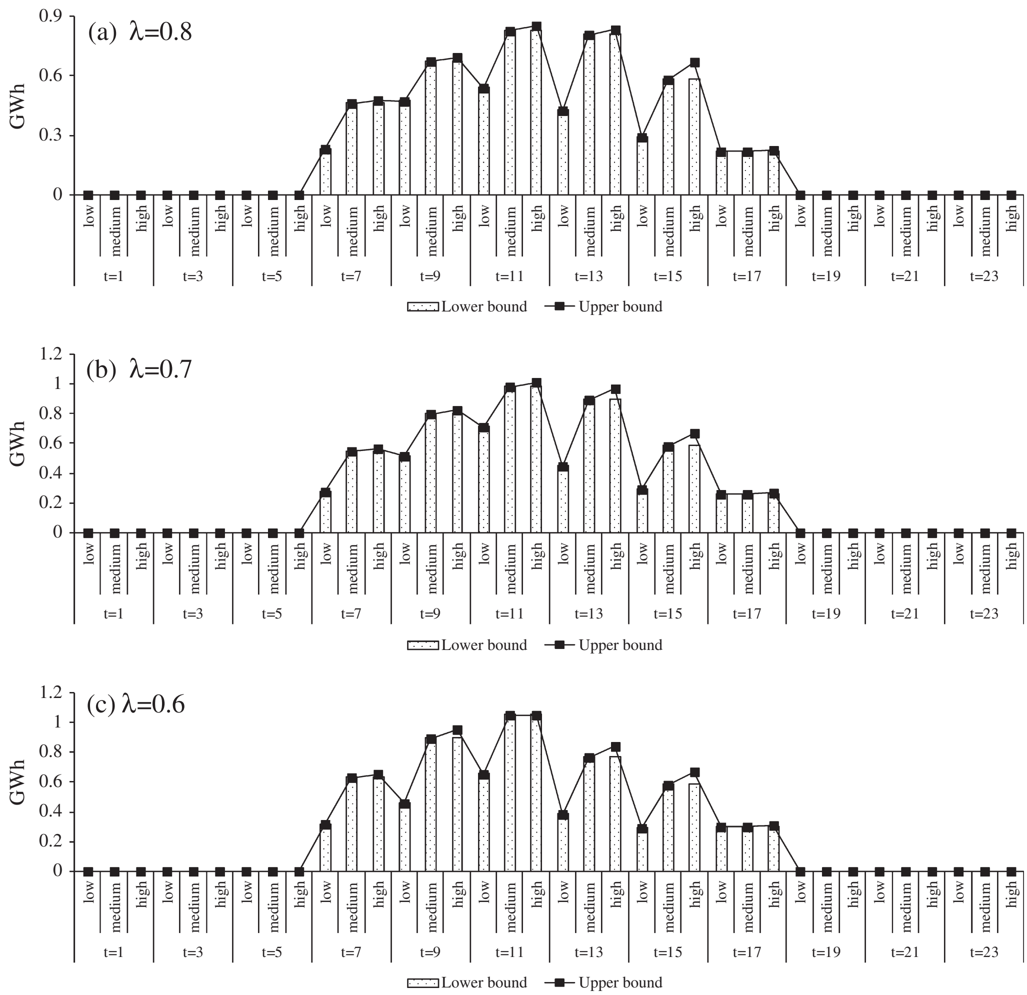

Fig. 10. Output of photovoltaic generation with 40% emission reduction goal under different confidence level.

lower risk of violating emission limitation), and a higher system reliability (and thus a lower risk of violating the availability of renewable energy sources). Moreover, when the decision makers have a moderate attitude towards system cost and environmental risk, these alternatives that represent a compromise between economic cost and environmental requirements would become more realistic. From Table 2, the results also demonstrate that the CO_2 mitigation contribute significantly to the electric power system adjustment, and different mitigation intensity do not much affect the renewable energy (solar power and wind power). In addition, the confidence level (higher forecasted value of renewable energy generation), would lead to a lower pre-designed traditional generation, which lower the system security when emergency occurs. In general, the provided scenarios represent multiple decision options with various economic and environmental considerations. Willingness to accept a desired electric power generation patterns, and CO_2 emission reduction under complex uncertainties will obtain an in-depth insights into the trade-offs between system economy and reliability.

Conclusion

This study considers pollution emission control on distributed energy generation operation management under generation and market uncertainties. A two-stage stochastic model combined with fuzzy chance-constrained programming was presented to optimize the electricity generation schedule. Day-ahead pre-designed generation schedule would be obtained through two-stage optimization considering the fluctuant real-time renewable generation. To better implement the environmental protection policy, the pollutants (SO_2, NO_x and PM) are under the real-time dynamic emission control and daily total amount control strategy for CO_2. The results illustrate that the proposed model can effectively control the trade-off between risk and system cost for electric system operation facing volatile energy markets and intermittent renewable energy. The electric system manager has always to make a compromise between the security degree and various system cost. With increasing renewable energy combined to the grid, there would be less pollutants and CO_2 emission; on the other hand, more reserve capacity should be supplied by traditional generators for the safety sake. Hence, different dispatch schedule should be provided with different confidence levels of constraints being specified, for the manager to choose.

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Appendix A. Nomenclatures for parameters and variables

$f^{\pm}$	Expected system cost over the planning periods (million dollar)
i	Index of energy resource; $i = 1$ for coal, $i = 2$ for natural gas, $i = 3$ for solar power, $i = 4$ for wind power, and $i = 5$ for imported electricity
t	Planning period; $t = 1, 2, \ldots, 24$
k	Type of power conversion technology; $k = 1$ for coal power generation, $k = 2$ for natural gas power generation, $k = 3$ for solar power, $k = 4$ for wind power
r	Type of contaminant; $r = 1$ for SO_2, $r = 2$ for NO_x, $r = 3$ for PM, r = 4 for CO_2
h	Level of power demand; $h = 1$ for low level, $h = 2$ for medium level, $h = 3$ for high level
Parameters	
p_h	Probability of scenario h
RC_k	Residual capacity of power generation technology k (GW)
$PR_{it}^{\pm}$	Price of energy source i during period t ($million/TJ)
$PV_{kt}^{\pm}$	Operation cost of technology k in period t ($million/GW h)
$PP_{kt}^{\pm}$	The operating cost for excess generation ($/GW h)
$PPE_t^{\pm}$	Power purchase price ($/GW h)
$CT_{krt}^{\pm}$	Pollutant treatment cost of pollutant r (dollar/kt)
$FE_{kt}^{\pm}$	Conversion efficiency of power generation technology k in period t (TJ/GW)
η_{kt}	Removal efficiency of pollutant r from power generation technology k
$SOT_{kt}^{\pm}, NOT_{kt}^{\pm}, POT_{kt}^{\pm}$ and $COT_{kt}^{\pm}$	SO_2, NO_x, PM, and CO_2 emission intensity of power generation technology k in period t (kt/GW h)
$ES_t^{\pm}, EN_t^{\pm}, EP_t^{\pm}$ and $EC_{kt}^{\pm}$	Total allowable SO_2, NO_x, PM, and CO_2 emissions in during period t (kt)
$ST_{kt}^{\pm}$	Working hours of power generation technology k in period t (h)
$\beta_k^{\pm}$	Conversion efficiency
$W_{kt\,\max}^{\pm}$	Maximum predefined electricity generation (GW h)
Decision variables	
$W_{kt}^{\pm}$	Predefined electricity generation according to load prediction (GW h)
$Q_{kth}^{\pm}$	Excess generated electricity by k in the second stage when the predefined generation unsatisfying the demand (GW h)
$IE_t^{\pm}$	Amount of imported electricity during period t (GW h)
$PD_{krt}^{\pm}$	Amount of pollutant generated by k (kiloton)
$ECO_{ht}^{\pm}$	Amount of CO_2 emission during period t (tonne)
$Z_{it}^{\pm}$	Amount of energy (TJ)

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