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An inexact optimization model for regional electric system steady operation management considering integrated renewable resources

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ABSTRACT

In this study, an inexact two-stage stochastic fuzzy programming (ITSFP) is developed for regional power generation planning with considering the intermittency and fuzziness of renewable energy power output. ITSFP incorporates interval-parameter programming (IPP), two-stage stochastic programming (TSP), and fuzzy credibility constrained programming (FCCP) within a general optimization framework which can tackle uncertainties expressed as intervals, probability distributions, and fuzzy sets. The developed method is applied to a regional electric power system over a one-day optimization horizon coupled with air pollution control. The power generation schemes, imported electricity, and system cost under various environmental goals and risk preferences are analyzed. The obtained results indicate that the model can provide a linkage between predefined electric power generation schedule and the relevant economic implications, as well as more reasonable decision alternatives for decision makers by loosening system constraints at specified confidence level. Besides, the fuzziness of forecast error corresponding to the variability of renewable energy resources could be effectively reflected. Moreover, the results are useful for addressing the trade-off between system economy and system risk.

1. Introduction

With the rapid development of economic and prompt growth of population, electric power consumption has been continuously increasing over the past decades. Meanwhile, electric power generation relied primarily on fossil fuels has brought serious environmental problems, such as excess atmospheric pollution discharge, greenhouse gas emission, and water pollution. For example, in China, the electric power industry was responsible for approximately 31.4% of the total SO_2 emissions in 2014, which would be likely to exacerbate air pollution and impose impacts direct and indirect on public health. In recent years, with the increasing severe environmental pollution and aggravated energy shortage crisis, environmental friendly renewable energy is deemed to be the most appropriate option to replace conventional energy resources, which is received more and more attention all over the world. However, there are some crucial limitations existing in the effective development and utilization of renewable energy, such as high levels of variability and uncertainty, low conversion efficiency and time mismatch with load demand for renewable power. Among those questions, the intrinsic intermittence and fluctuation would cause the fuzziness and uncertainty of power output, resulting in difficulty for formulating efficient generation schedules and serious consequences to the dynamic economic dispatch in regional power grid [1–5]. Moreover, in regional electric power systems, varieties of processes corresponding to electricity generation, import/export distribution, as well as economic parameters associated with uncertainties and complexities should be considered by decision makers simultaneously [6–10]. Therefore, it is desired to develop an effective tool for dealing with uncertainties, reflecting better renewable energy operation characteristics, and modeling electric power system management considering pollutants emission control.

Previously, a significant amount of systems analysis techniques were employed for solving those generation scheduling problems. For example, Moura and de Almeida [11] developed a novel multi-objective optimization model for renewable energy system operation management considering demand-side management and response technologies. Considine and Larson [12] developed a

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system economic model for short term power generation technologies switching or substitution coupled with carbon cap and trade by introducing the European Union's emissions trading system. Ippolito et al. [13] proposed a multi-objective optimized management model of electrical energy storage systems for an existing islanded distribution network with renewable energy sources in the Mediterranean Sea. Guo et al. [14] presented an optimal model for power generation dispatch, where wind and coal-fired power generation technologies were integrated in a regional electric power system. Taha et al. [15] developed a bi-level multi-period optimization programming for a micro-grid system operation management under consideration of quasi-feed-in-tariff policy. Jebaraj et al. [16] presented an optimal model for electricity allocation and sustainable resource utilization in India. Based on predicted renewable generation and market information, Chen and Garcia [17] developed a generic methodology for the operations optimization of hybrid energy systems. Álvarez-Miranda et al. [18] proposed a novel scenario-based approach for wind power generation management, where dynamic characteristic of forecasting process and robust unit commitment policies were taken into account. Yuan et al. [19] developed a hybrid model for a short-term wind power forecasting based on the least squares support vector machine, which was optimized using gravitational search algorithm.

In addition, in order to tackle the interrelated complexities existing in the electric power system, especially the uncertainties for renewable energy resources, a series of inexact optimization approaches have been developed in recent years, that include interval-parameter programming, stochastic mathematical programming (e.g. two-stage stochastic programming, multi-stage stochastic programming, stochastic robust programming, chance-constraint programming), fuzzy mathematical programming, and interacted methods [20–23]. Among these methods, interval two-stage stochastic programming (ITSP) model, incorporated interval-parameter programming (IPP) and two-stage stochastic programming (TSP), is a potential approach for electric power planning and receive much attention [24–26]. It can handle multiple uncertainties expressed as discrete intervals and known probability distributions in a model's both sides and achieve management strategy adjustment after real events happened. Moreover, ITSP method could provide an effective way for tackling decision problems, where synthetic analysis of different policy scenarios is desired. For example, Chen et al. [27] proposed a two-stage inexact-stochastic programming model for CO_2-emission trading management. However, in a coupled traditional and renewable power generation system, the fluctuation of wind and solar power output poses a grave threat to electric power dispatch, wherein power load forecast is extremely expected [28]. In general, due to the lack of long time sequenced climate and meteorological information, load forecast are usually estimated by fuzzy information with different confidence levels through analyzing large scale meteorology data. In addition, forecast error would appear unavoidably in the forecasting process, and should be incorporated into generation scheduling process by decision makers to reduce its effect. However, ITSP method could not adequately reflect those characteristics of renewable power generation, and bring forecast errors into the optimization model. The drawback would lead to the loss of vague information as well as unreliable solutions when dealing with electric power generation scheduling problems, especially in traditional and renewable power generation system.

Fuzzy credibility constraints programming (FCCP) is a generally accepted fuzzy mathematical programming method that can tackle uncertain information identified as fuzzy sets within a measure of confidence level [29]. It would not only help decision makers to quantitatively evaluate trade-offs between economic objectives and system risks existing in the dispatch scheduling process, but also provide compromising schemes for managers regarding the safety of fuzzy constraints with various credibility satisfaction level. Especially, it is a novel method for reflecting the fuzziness of forecast error in decision-making. FCCP had been successfully applied in many real-world practices, which was mostly attributable to its advantages in capturing the ambiguous uncertainties and enlarging the uncertain decision space. For example, Ji et al. [30] proposed a hybrid inexact stochastic-fuzzy chance-constrained programming for pollutants and CO_2 emissions management in a regional micro-grid system over a one-day horizon. Rong and Lahdelma [31] presented a fuzzy chance constrained linear programming model for scrap charge optimization of steel production. Based on integer fuzzy credibility constrained programming method, Zhang et al. [32] advanced an inexact optimization model for regional power system management. Nevertheless, FCCP method has limitations in tackling uncertain parameters that exist in the model's left-hand sides and coefficients, and reflecting the random characteristics in electric power generation system. One potential approach is to integrate ITSP and FCCP method within a general optimization framework to handle these issues.

Therefore, the objective of this paper is to develop an inexact two-stage stochastic fuzzy programming model for regional electric power system steady operation management considering pollutants emission control, which will incorporate interval-parameter programming, two-stage stochastic programming, and fuzzy credibility constrained programming. It can effectively address uncertainties expressed as interval parameters, probability distributions, and fuzzy sets. In the model, the fluctuation for renewable power output can be incarnated as the fuzziness of forecast error by transforming the fuzzy credibility constraints into their crisp equivalent forms. The model will be applied to a planning of power generation scheduling in regional electric power system over a one-day horizon under consideration of air pollutant control and renewable energy power applications. The modeling results can help decision makers acquire multiple optimal alternatives and applicable solutions, and also gain a comprehensive trade-off between system economy and reliability risk.

2. Methodology

2.1. Interval two-stage stochastic programming

Two-stage stochastic programming (TSP) is available for handling problems where an analysis of different policy scenarios is conceivable and uncertain coefficients are random with known probability distributions. A TSP model can be described as follows [33]:

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

subject to:

$$A_r X \le B_r,\ \ r \in M, M = 1, 2, ..., m_1 \tag{1b}$$

$$A_i X + A_i^{'} Y \ge \tilde{w}_{ih}, i \in M; M = 1, 2, ..., m_2; h = 1, 2, ..., s \tag{1c}$$

$$x_j \ge 0,\ \ x_j \in X, j = 1, 2, ..., n_1 \tag{1d}$$

$$y_{jh} \ge 0,\ \ j_{jh} \in Y, j = 1, 2, ..., n_2; h = 1, 2, ..., s \tag{1e}$$

where x_j and y_{jh} represent the first- and second-stage decision variables, respectively; $C_{T_1}X$ denotes the first-stage costs or benefits; h is the scenario of the random events happening; p_h is the probability levels; $\tilde{w}_{ih}$ is the discrete values of random variables, where $h=1,2,...,s$ and $\sum p_h = 1$; $\sum_{h=1}^{s} p_h D_{T_2} Y$ is the expected value of second-stage system penalties.

TSP model can effectively tackle probabilistic uncertainties in the constraint's right-hand sides, and capture dynamic feature and economic penalties expressed as recourse or corrective measures. However, it is incapable of addressing independent uncertainties existing in the model's left-hand sides. Meanwhile, interval-parameter programming (IPP) can address uncertainties in the model's left and right-hand sides and objective function without being quantified as membership or distribution functions. This leads to an interval two-stage stochastic programming (ITSP) model as follows:

$$\min\ f^{\pm} = C_{T_1}^{\pm} X^{\pm} + \sum_{h=1}^{s} p_h D_{T_2}^{\pm} Y^{\pm} \tag{2a}$$

subject to:

$$A_r^{\pm} X^{\pm} \le B_r^{\pm},\ \ r \in M, M = 1,2,...,m_1 \tag{2b}$$

$$A_i^{\pm} X^{\pm} + A_i^{\pm'} Y^{\pm} \ge \tilde{w}_{ih}^{\pm},\ \ i \in M; M = 1,2,...,m_2; h = 1,2,...,s \tag{2c}$$

$$x_j^{\pm} \ge 0,\ \ x_j^{\pm} \in X^{\pm}, j = 1,2,...,n_1 \tag{2d}$$

$$y_{jh}^{\pm} \ge 0,\ \ y_{jh}^{\pm} \in Y^{\pm}, j = 1,2,...,n_2; h = 1,2,...,s \tag{2e}$$

2.2. Fuzzy credibility constrained program

Fuzzy credibility constrained programming (FCCP) is an alternative tool for dealing with problems where uncertainties are expressed as fuzzy sets. It could enlarge decision space for managers by means of not requiring the constraints in which the fuzzy variables exist to be totally satisfied in a certain degree. A FCCP model can be expressed as follows [34]:

$$\min\ f(x,\xi) \tag{3a}$$

subject to:

$$Cr\left\{\sum_{j=1}^{n} g_j(x,\xi) \le 0, j = 1,2,...,n\right\} \ge \lambda_j \tag{3b}$$

$$x \ge 0 \tag{3c}$$

where x is vector of decision variables; ξ denotes vector of fuzzy variables; λ_j is the fuzzy confidence level; $Cr\{\bullet\}$ represents the credibility of the event $\{\bullet\}$. Formula (3b) denotes that credibility of satisfying $g_j(x,\xi) \ge 0$ should be not less than level λ_j.

In FCCP, credibility constraints can be handled through credibility measures defined by possibility measure and necessity measure as shown in (4) and (5) [5,35].

$$Pos\{\xi \le r\} = \sup_{u \le r} \mu(u) \tag{4}$$

$$Nec\{\xi \le r\} = 1 - Pos\{\xi > r\} = 1 - \sup_{u > r} \mu(u) \tag{5}$$

where ξ is a fuzzy variable with membership function μ; Pos and Nec represent the possibility measure and necessity measure, respectively. The credibility measure Cr is an average of the possibility measure and the necessity measure [30,32,and36]:

$$Cr\{\xi \le r\} = \frac{1}{2}\left(Pos\{\xi \le r\} + Nec\{\xi \le r\}\right) \tag{6}$$

In the hourly wind and solar power output forecast, there are always errors in these forecasted values, which can be formulated as follows [37]:

$$\varepsilon_W\% = \frac{P_W - P_W'}{P_W'} \times 100\% \tag{7}$$

where ε_W denotes the percentage error in forecast, P_W is the actual power output while P_W' is the power forecast. In order to reflect the degree of accuracy of errors, the membership function of forecast error expressed as Cauchy distribution can be used, which is depicted as follows [5]:

$$\mu = \begin{cases} \dfrac{1}{1+\sigma(\varepsilon_W/E_{W+})^2}, & \varepsilon_W > 0 \\ \dfrac{1}{1+\sigma(\varepsilon_W/E_{W-})^2}, & \varepsilon_W \le 0 \end{cases} \tag{8}$$

where E_{W+} is the average value of positive percentage error when the actual power output is greater than the power forecast, E_{W-} is the average value of negative percentage error when the actual load is smaller than the forecast one; σ denotes the weighting factor. Then, based on the above models, the credibility measure of power forecast can be expressed as follows:

$$Cr\{\xi \le r\} = \begin{cases} 1 - \dfrac{1}{2\left[1+\sigma(\varepsilon_W/E_{W+})^2\right]}, & \varepsilon_W > 0 \\ \dfrac{1}{2\left[1+\sigma(\varepsilon_W/E_{W-})^2\right]}, & \varepsilon_W \le 0 \end{cases} \tag{9}$$

Let $g_j(x,\xi)$ be replaced by $h_j(x) - \xi_j$, where ξ_j denotes a fuzzy variable, the necessary and sufficient condition of $Cr\{\sum_{j=1}^{n} g_j(x,\xi) \le 0\} \ge \lambda_j$ is that $h_j(x) \ge K_{\lambda_j}$, where K_{λ_j} is described as follows [38]:

$$K_{\lambda_j} = \begin{cases} \sup\left\{K \middle| K = \mu^{-1}(2\lambda_j)\right\} & \lambda_j < 1/2 \\ \inf\left\{K \middle| K = \mu^{-1}(2(1-\lambda_j))\right\} & \lambda_j \ge 1/2 \end{cases} \tag{10}$$

Normally, an acceptable credibility level is not less than 0.5. Thus, based on equation (10), for each $1 > \lambda_j \ge 0.5$, the following equation can be acquired:

$$K_{\lambda_j} = |E_{W-}|\sqrt{\frac{2\lambda_j - 1}{2\sigma_j(1-\lambda_j)}} \tag{11}$$

Therefore, according to the above transformation, the model (3) can be expressed as a crisp equivalent model:

$$\min\ f(x,\xi) \tag{12a}$$

subject to:

$$h_j(x) \le |E_{W-}|\sqrt{\frac{2\lambda_j - 1}{2\sigma_j(1-\lambda_j)}} \tag{12b}$$

$$x \ge 0 \tag{12c}$$

2.3. Inexact two-stage stochastic fuzzy programming

Apparently, model (2) can efficiently address multiple uncertainties presented as intervals and probability distributions. Nevertheless, with regard to other parameters described by fuzzy sets in the system constraints, it would be infeasible. Therefore, one potential approach to reflect such complexities is to integrate FCCP and ITSP within a general framework. This leads to an inexact two-stage stochastic fuzzy credibility constrained programming (ITSFP) model as follows:

$$\min\ f^{\pm} = C^{\pm}_{T_1}X^{\pm} + \sum_{h=1}^{s} p_h D^{\pm}_{T_2} Y^{\pm} \tag{13a}$$

subject to:

$$Cr\left\{A^{\pm}_{r}X^{\pm} \le \tilde{B}^{'\pm}_{r}(1+\xi_r)\right\} \ge \lambda^{\pm}_{r},\ \ r\in M, M = 1,2,...,m_1 \tag{13b}$$

$$A^{\pm}_{i}X^{\pm} + A^{\pm'}_{i}Y^{\pm} \ge \tilde{w}^{\pm}_{ih},\ \ i\in M; M = 1,2,...,m_2; h = 1,2,...,s \tag{13c}$$

$$x^{\pm}_{j} \ge 0,\ \ x^{\pm}_{j}\in X^{\pm}, j = 1,2,...,n_1 \tag{13d}$$

$$y^{\pm}_{jh} \ge 0, y^{\pm}_{jh}\in Y^{\pm}, j = 1,2,...,n_2; h = 1,2,...,s \tag{13e}$$

where $\tilde{B}^{'\pm}_{r}$ is the forecast value, ξ_r is the percentage error in forecast, $\lambda^{\pm}_{r}$ is the confidence level.

For model (13), if $x^{\pm}_{j}$ are regarded as uncertain inputs, the existing methods may be infeasible when dealing with inexact linear programming problems. In this study, an optimized set of target values can be identified by having μ_j in model (13). Accordingly, let $x_j = x^{-}_{j} + \mu_j\Delta x_j$, where $\Delta x_j = x^{+}_{j} - x^{-}_{j}$ and $\mu_j\in[0,1]$, μ_j are decision variables and can be used to identify an optimized set of target values $x^{\pm}_{j}$ where related policy can be analyzed. The detailed solution method for solving the ITSFP model is presented in Appendix A.

3. Case study

3.1. Overview of the study area

Consider a hypothetical and representative case wherein electric power system in a regional micro-grid is responsible for satisfying end-users' requirements. Along with the exhaustion of traditional fossil energy resources and aggravation of environmental pollution problems, renewable energy sources would undoubtedly be the primary option for mitigating the contradiction between electricity supply/demand and emission reduction goals. In this system (as shown in Fig. 1), two conventional energy resources (i.e., coal and natural gas) and two renewable energy resources (i.e., wind and solar) are served with limited availabilities. The regional electricity power supply include coal-fired power, natural gas-fired power, wind power, and solar power with a residual capacity of 1.50 GW, 1.00 GW, 0.95 GW, and 0.75 GW, respectively. Imported power from the main grid is available to compensate supply shortage of regional power grid, when the power-generation capacity cannot meet the electricity demand. Moreover, a mass of environmental pollutants (e.g., sulfur dioxide (SO_2), nitrogen oxides (NOx), and particulate matter (PM)) would be discharged and affect atmospheric environmental quality during electricity generation process, which should be early controlled to meet the stricter environmental standard.

In the electric power system, the problem can be formulated as minimizing the cost of regional electric power system for hourly power generation scheduling. Based on the power-generation capacity and load demand, day-ahead generation targets in different power plants are pre-regulated. If the pre-regulated generation targets can meet the real-time demand, the system will encounter with the regular cost; on the contrary, if the targets are exceeded, it will result in penalties on the excess cost from the extra power generation and management. Besides, the system is fraught with multiple uncertainties related to energy resource supply, electricity generation, power load demand, and pollutants emission control, as well as various economic and technical parameters (e.g., generation targets, cost parameters, and emission rate). The complexities and uncertainties could affect the generation scheduling and the associated optimization processes, which should be comprehensively considered by decision makers. Furthermore, due to the dynamic features of wind and solar energy in accordance with the wind speed and solar radiation, the power output of wind farm and photovoltaic panels will fluctuate and be difficult to be obtained precise values. The volatile and intermittent characteristics of wind and solar power would pose serious challenges to power grid dispatch, and impede large-scale wind and solar power to connect to power grid. Moreover, in order to meet the increasingly environmental requirements, decision makers should adopt a series of measures to control pollutants emission in the system management.

Therefore, the study's task is to: (1) identify multiple complexities and uncertainties existing in the regional electric power system; (2) tackle the fuzzy problems of wind and solar power output; (3) formulate optimal electricity generation scheduling for conventional and renewable energy power conversion technologies under different pollution reduction plans; and (4) generate decision alternatives by analyzing the trade-off between economic objectives, environmental requirements and system risks.

3.2. Model formulation

According to the above analysis, the developed inexact two-stage stochastic fuzzy programming (ITSFP) method is suitable for regional electric power system management. The method can effectively reflect multiple uncertainties described as intervals, probability distributions and fuzzy sets. Moreover, the model can be helpful to handle the precision problems of wind and solar power forecast by converting the fuzziness of power output into forecast error. The objective of this study is to acquire alternative plans for various power generation activities by minimizing the system cost over a 24-h planning horizon. The system constraints mainly involve mass balance for conventional and renewable energy, pollution emission limitations, electricity demand balance, and technical restrictions. Thus, the model can be formulated as follows:

$$\begin{aligned} f^{\pm} = & \sum_{k=1}^{2}\sum_{t=1}^{24}\sum_{h=1}^{3} EC^{\pm}_{kt}\cdot\left(X^{\pm}_{kt} + p_{th}\cdot Q^{\pm}_{kth}\right)\cdot CG^{\pm}_{kt} + \sum_{k=1}^{4}\sum_{t=1}^{24} PV^{\pm}_{kt}\cdot X^{\pm}_{kt} \\ & + \sum_{k=1}^{4}\sum_{t=1}^{24}\sum_{h=1}^{3} p_{th}\cdot PP^{\pm}_{kt}\cdot Q^{\pm}_{kth} + \sum_{t=1}^{24}\sum_{h=1}^{3} p_{th}\cdot IE^{\pm}_{t}\cdot IP^{\pm}_{th} + \sum_{k=1}^{4} \\ & \times \sum_{r=1}^{3}\sum_{t=1}^{24} CE^{\pm}_{krt}\cdot X^{\pm}_{kt}\cdot\eta^{\pm}_{krt}\cdot EF^{\pm}_{krt} + \sum_{k=1}^{4}\sum_{r=1}^{3}\sum_{t=1}^{24} \\ & \times \sum_{h=1}^{3} p_{th}\cdot PE^{\pm}_{krt}\cdot Q^{\pm}_{kth}\cdot\eta^{\pm}_{krt}\cdot EF^{\pm}_{krt} \end{aligned} \tag{14a}$$

subject to:

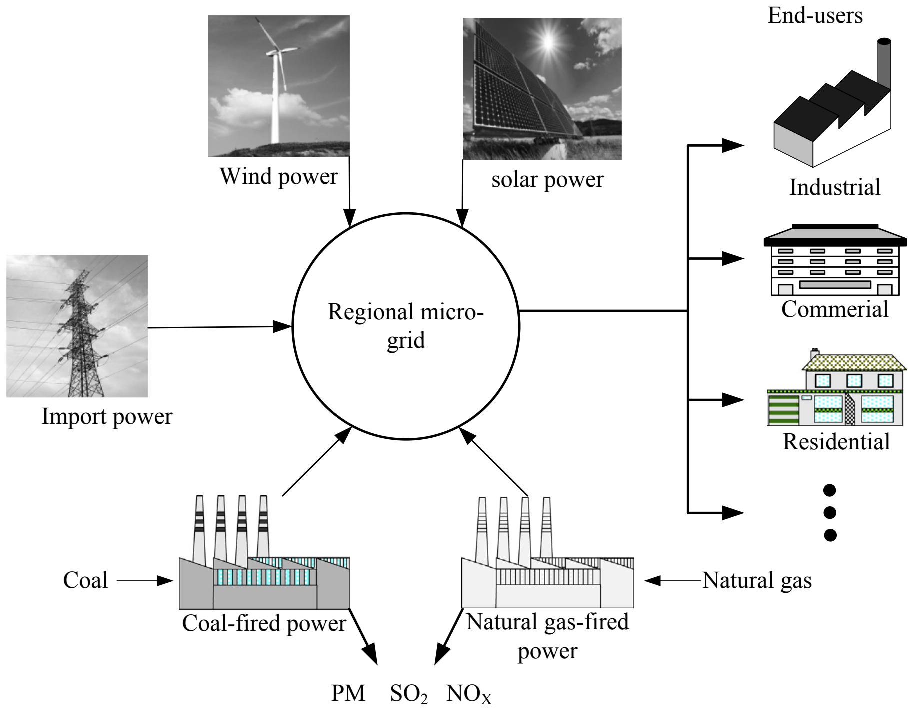

Fig. 1. The schematic of reginal electric power system under study.

(1) Constraints for coal balance

$$(X_{1t}^{\pm} + Q_{1th}^{\pm}) \cdot CG_{1t}^{\pm} \le UPC_t^{\pm}, \quad \forall t, h \tag{14b}$$

(2) Constraints for natural-gas balance

$$(X_{2t}^{\pm} + Q_{2th}^{\pm}) \cdot CG_{2t}^{\pm} \le UPN_t^{\pm}, \quad \forall t, h \tag{14c}$$

(3) Constraint for wind power

$$Cr\left\{X_{3t}^{\pm} + Q_{3th}^{\pm} \le PW_t' \cdot (1 + \xi_w)\right\} \ge \lambda^{\pm}, \quad \forall t, h \tag{14d}$$

(4) Constraint for solar power

$$Cr\left\{X_{4t}^{\pm} + Q_{4th}^{\pm} \le SW_t' \cdot (1 + \xi_s)\right\} \ge \lambda^{\pm}, \quad \forall t, h \tag{14e}$$

(5) Constraint for electricity supply and demand balance

$$\sum_{k=1}^{4} (X_{kt}^{\pm} + Q_{kth}^{\pm}) + IP_{th}^{\pm} \ge DM_{th}^{\pm}, \quad \forall t, h \tag{14f}$$

(6) Constraints for electricity generation

$$RC_k \cdot ST_{kt}^{\pm} \ge X_{kt}^{\pm} + Q_{kth}^{\pm}, \quad \forall k, t, h \tag{14g}$$

$$X_{kt}^{\pm} \ge Q_{kth}^{\pm}, \quad \forall k, t, h \tag{14h}$$

(7) Constraints for environment

$$\sum_{k=1}^{4} (X_{kt}^{\pm} + Q_{kth}^{\pm}) \cdot \left(1 - \eta_{krt}^{\pm}\right) \cdot EF_{krt}^{\pm} \le ES_{rt}^{\pm}, \quad \forall t, r, h \tag{14i}$$

(8) Nonnegative constraints

$$Q_{kth}^{\pm} \ge 0, \quad \forall k, t, h \tag{14j}$$

The detailed nomenclatures for the variables and parameters are presented in Appendix B.

3.3. Data collection and scenarios analysis

In the study, electric power generated from various power conversion technologies in the region would be self-consumed. Besides, wind and solar power output could be fully dispatched without transmission loss. In addition, the study would not consider the specific power prediction method, but adopt the research results of forecast error according to the related references [5,37]. Table 1 shows the potential power demands under different scenarios in a typical working day of July in summer, which are expressed as interval numbers with given probability levels. Wind and solar power forecast values are shown in Fig. 2. Three scenarios related to different environmental management policies are designed. Scenario 1 means that the gross of pollutants emission are confined with a certain quantity over the planning horizon. Scenario 2 represents that the pollutants emission is to be mitigated by 10% based on scenario 1. Scenario 3 denotes the mitigation level will be 15%.

4. Results analysis and discussion

Solutions of the proposed model are displayed under different confidence levels (λ = 0.9, 0.8, 0.7, and 0.6) and three pollutants emission scenarios. Table 2 presents the pre-designed power

Table 1
Original hourly load demand.

Electricity load demand (GWh)	Demand level		
	L	M	H
	0.2	0.55	0.25
t = 1	[1.98,2.50]	[2.23,2.98]	[2.70,3.38]
t = 2	[1.90,2.43]	[2.13,2.94]	[2.58,3.30]
t = 3	[1.78,2.20]	[2.03,2.68]	[2.46,3.18]
t = 4	[1.70,1.93]	[1.96,2.43	[2.33,2.93]
t = 5	[1.65,1.83]	[1.85,2.29]	[2.21,2.78]
t = 6	[1.59,1.90]	[1.81,2.35	[2.28,2.85]
t = 7	[1.78,2.05]	[2.00,2.53]	[2.55,2.91]
t = 8	[2.10,2.23]	[2.38,2.76]	[2.84,3.20]
t = 9	[2.30,2.50]	[2.60,3.00]	[3.00,3.53]
t = 10	[2.42,2.80]	[2.73,3.28]	[3.11,3.75]
t = 11	[2.60,2.95]	[2.91,3.40]	[3.30,3.93]
t = 12	[2.72,3.03]	[3.05,3.49]	[3.41,3.98]
t = 13	[2.81,3.10]	[3.13,3.58]	[3.50,4.13]
t = 14	[2.92,3.22]	[3.22,3.73]	[3.60,4.23]
t = 15	[2.70,3.13]	[3.14,3.66]	[3.49,4.05]
t = 16	[2.55,2.95]	[2.96,3.43]	[3.30,3.93]
t = 17	[2.20,2.65]	[2.60,3.16]	[2.99,3.68]
t = 18	[2.13,2.58]	[2.45,3.01]	[2.91,3.48]
t = 19	[2.23,2.70]	[2.55,3.15]	[3.05,3.65]
t = 20	[2.37,2.88]	[2.68,3.36]	[3.18,3.84]
t = 21	[2.32,2.77]	[2.64,3.22]	[3.08,3.68]
t = 22	[2.22,2.73]	[2.53,3.19]	[2.96,3.63]
t = 23	[2.16,2.65]	[2.44,3.12]	[2.88,3.57]
t = 24	[2.05,2.58]	[2.33,3.03]	[2.78,3.48]

generation targets under different scenarios with λ fixed as 0.9. Generally, the optimized pre-regulated coal-fired power generation would decrease as raising the mitigation levels; conversely, the natural gas-fired generation would increase lightly. For example, under scenario 1, the pre-regulated coal-fired power generation would be 1.200, 1.329, and 1.220 GWh at 1:00, 14:00 and 24:00, respectively; under scenario 3, it would be 1.130, 1.117, and 1.117 GWh accordingly. This is mainly because coal-fired power possesses the characteristic of higher emission rate. Thus, the decision makers would have to promise lower quantities in order to meet emission reduction requirements. By contrast, natural gas is a cleaner energy resource, and the pre-regulated natural gas-fired power generation would rise from 0.480, 0.480, and 0.580 GWh under scenario 1 to 0.554, 0.648, and 0.650 GWh under scenario 3 at 1:00, 14:00 and 24:00, respectively. At the meanwhile, due to the feature of near-zero pollutants emission, the pre-regulated wind and solar power generation would increase at certain times. Taken wind power as an example, the pre-regulated power generation amount at 9:00 and 15:00 would be 0.298 and 0.583 GWh under scenario 1, and 0.325 and 0.680 GWh under scenario 3, respectively. Though wind power and solar power hardly produce air pollution compared with the conventional power generation, they have higher operating cost. In the system, if all the energy produced by wind or solar power fully used in the system, the total system cost may be very high; this would lead to serious negative side effects on the local economy. Therefore, when considering the system objective, decision makers would have to synthetically analyze the trade-off between the system cost and environmental requirements, and the production of wind and solar power would be used partly under disadvantageous situations.

Table 3 shows the excess power generation amount with different λ levels under scenario 1. If the pre-designed power generation targets cannot satisfy end-users' requirements, it would lead to the deficit. It could be observed that the excess generation quantities for coal-fired power, wind, and solar power would vary under different electricity demand levels. For natural gas-fired power, electricity shortage would occur when the load demand level is high. In addition, with λ level decreasing, the excess power generation for wind and solar power would decrease simultaneously. For example, the excess solar power generation at 12:00 would be [0, 0.305], [0.204, 0.309], and [0.291, 0.309] GWh under low, medium and high demand levels with λ = 0.9, respectively; under λ setting as 0.6, it would be [0, 0.196], 0.196, and 0.196 GWh, correspondingly. The reason is that the lower confidence level corresponds to a lower availability of solar energy resource, thus the forecast output of solar power would be lower and excess power generation would be less accordingly. Unlike the situation for renewable energy, the excess coal-fired power generation would be stable as confidence level increasing, indicating that the changes of confidence levels would make no difference to the excess coal-fired power generation under different electricity demand levels. For natural gas-fired power, the excess power generation would not change obviously. For instance, under different electricity demand levels, it would be 0, 0, and 0.214 GWh with λ fixed as 0.9 at 16:00, and 0, 0.098, and 0.214 GWh with λ fixed as 0.6, respectively.

Fig. 3 shows the optimal power generation schemes for different power conversion technologies under scenario 1 with λ fixed as 0.8. Due to the comparatively lower purchasing price and operation cost, coal-fired power would play a significant role in power generation activities, whose optimized power generation quantity would have a larger proportion in the total electricity supply. Generally, the optimal coal-fired power generation in each hour would show a stable trend. However, the amount of power generation at 6:00 is an exception, which would be relatively lower. This is mainly because the load demand would be in its valley hour that would not need amounts of electricity supply. For natural gas-fired

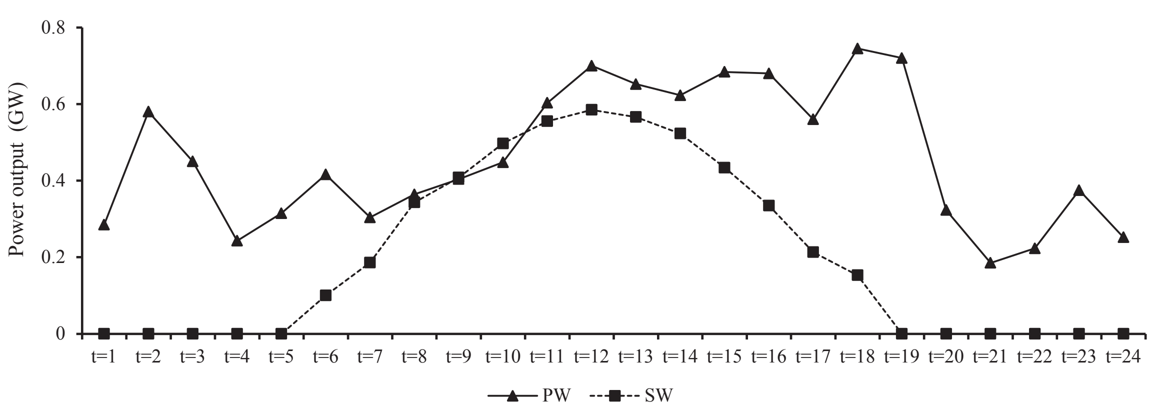

Fig. 2. Output forecast of wind power and solar power.

Table 2
Pre-designed hourly power generation targets under different scenarios ($\lambda = 0.9$).

Time (h)	Optimized generation target $X_{kt\ opt}$(GWh)											
	Scenario 1				Scenario 2				Scenario 3			
	k = 1	k = 2	k = 3	k = 4	k = 1	k = 2	k = 3	k = 4	k = 1	k = 2	k = 3	k = 4
t = 1	1.200	0.480	0.295	0	1.196	0.484	0.295	0	1.130	0.554	0.295	0
t = 2	1.002	0.420	0.478	0	1.002	0.420	0.478	0	1.002	0.420	0.478	0
t = 3	1.015	0.420	0.345	0	1.015	0.420	0.345	0	1.015	0.420	0.345	0
t = 4	1.112	0.400	0.180	0	1.120	0.400	0.180	0	1.120	0.400	0.180	0
t = 5	1.005	0.400	0.245	0	1.005	0.400	0.245	0	1.005	0.400	0.245	0
t = 6	0.792	0.400	0.335	0.063	0.792	0.400	0.335	0.063	0.792	0.400	0.335	0.063
t = 7	1.029	0.420	0.214	0.117	1.029	0.420	0.214	0.117	1.029	0.420	0.214	0.117
t = 8	1.174	0.450	0.260	0.216	1.174	0.450	0.260	0.216	1.130	0.450	0.260	0.260
t = 9	1.220	0.450	0.298	0.332	1.196	0.450	0.298	0.356	1.130	0.450	0.325	0.395
t = 10	1.260	0.450	0.345	0.365	1.196	0.450	0.345	0.429	1.130	0.450	0.360	0.480
t = 11	1.224	0.480	0.488	0.408	1.196	0.480	0.488	0.436	1.130	0.480	0.488	0.502
t = 12	1.252	0.480	0.560	0.428	1.196	0.480	0.560	0.484	1.130	0.480	0.560	0.550
t = 13	1.329	0.480	0.520	0.481	1.196	0.480	0.600	0.534	1.130	0.496	0.650	0.534
t = 14	1.329	0.480	0.606	0.500	1.196	0.569	0.650	0.500	1.117	0.648	0.650	0.500
t = 15	1.329	0.450	0.583	0.338	1.196	0.450	0.634	0.420	1.130	0.470	0.680	0.420
t = 16	1.328	0.450	0.547	0.220	1.196	0.450	0.572	0.327	1.130	0.450	0.638	0.327
t = 17	1.236	0.420	0.410	0.134	1.196	0.420	0.410	0.174	1.130	0.420	0.450	0.200
t = 18	1.014	0.420	0.595	0.096	1.014	0.420	0.595	0.096	1.014	0.420	0.595	0.096
t = 19	1.200	0.450	0.580	0	1.196	0.450	0.584	0	1.130	0.450	0.650	0
t = 20	1.323	0.700	0.320	0	1.181	0.700	0.320	0	1.109	0.700	0.320	0
t = 21	1.320	0.680	0.180	0	1.184	0.680	0.180	0	1.112	0.680	0.180	0
t = 22	1.329	0.650	0.220	0	1.188	0.650	0.220	0	1.117	0.650	0.220	0
t = 23	1.200	0.587	0.368	0	1.196	0.591	0.368	0	1.117	0.650	0.368	0
t = 24	1.220	0.580	0.250	0	1.195	0.605	0.250	0	1.117	0.650	0.250	0

Table 3
Excess power generation quantities under different λ levels (Scenario 1).

	Time	$\lambda = 0.9$			$\lambda = 0.8$			$\lambda = 0.6$		
		L	M	H	L	M	H	L	M	H
k = 1	t = 4	[0,0.230]	[0.211,0.286]	[0.209,0.278]	[0,0.230]	[0.211,0.286]	[0.209,0.278]	[0,0.230]	[0.211,0.286]	[0.209,0.278]
	t = 8	0	[0.157,0.232]	[0.155,0.225]	0	[0.146,0.221]	[0.144,0.209]	0	[0.146,0.221]	[0.144,0.209]
	t = 12	0	[0.078,0.148]	[0.078,0.148]	[0,0.054]	[0.078,0.148]	[0.077,0.148]	[0,0.109]	[0.078,0.148]	[0.077,0.125]
	t = 16	[0,0.078]	[0.003,0.078]	[0.001,0.700]	[0,0.078]	[0.003,0.078]	[0.001,0.070]	[0,0.078]	[0.002,0.078]	[0.001,0.070]
	t = 20	[0,0.074]	[0,0.074]	[0,0.074]	[0,0.074]	[0,0.074]	[0,0.074]	[0,0.074]	[0,0.074]	[0,0.074]
	t = 24	[0,0.185]	[0.109,0.178]	[0.109,0.178]	[0,0.185]	[0.109,0.178]	[0.109,0.178]	[0,0.185]	[0.109,0.178]	[0.109,0.178]
k = 2	t = 4	0	0	0.220	0	0	0.222	0	0	0.222
	t = 8	0	0	0.165	0	0	0.187	0	0	0.187
	t = 12	0	0	0	0	0	0.110	0	0	0.118
	t = 16	0	0	0.214	0	0.002	0.214	0	0.098	0.214
	t = 20	0	0	0	0	0	0	0	0	0
	t = 24	0	0.084	0.084	0	0.084	0.084	0	0.084	0.084
k = 3	t = 4	0	[0.049,0.126]	0.126	0	[0.049,0.102]	0.102	0	[0.049,0.079]	0.079
	t = 8	0	[0,0.199]	[0.198,0.199]	0	[0,0.162]	[0.139,0.162]	0	[0,0.128]	0.128
	t = 12	0	[0,0.313]	[0.219,0.322]	0	[0,0.252]	[0.211,0.252]	0	[0.056,0.186]	0.186
	t = 16	[0,0.124]	[0.210,0.310]	0.310	[0,0.158]	0.242	0.242	0	0.178	0.178
	t = 20	[0.022,0.087]	0.087	0.087	[0.022,0.055]	0.055	0.055	0.022	0.024	0.024
	t = 24	[0,0.068]	0.068	0.068	[0,0.042]	0.042	0.042	0	0.186	0.186
k = 4	t = 4	0	0	0	[0,0.130]	[0,0.193]	[0,0.193]	0	0	0
	t = 8	[0,0.130]	[0,0.216]	[0.117,0.216]	[0,0.106]	[0,0.106]	0.106	[0,0.088]	[0,0.088]	0.088
	t = 12	[0,0.305]	[0.204,0.309]	[0.291,0.309]	[0,0.251]	[0.203,0.251]	[0.236,0.251]	[0,0.196]	0.196	0.196
	t = 16	[0,0.202]	0.202	0.202	[0,0.169]	0.169	0.169	[0,0.137]	0.137	0.137
	t = 20	0	0	0	0	0	0	0	0	0
	t = 24	0	0	0	0	0	0	0	0	0

power, the power generation would maintain at a higher level during 20:00–24:00. The power curves of wind and solar power would fluctuate significantly over the planning horizon attributed to the influence of weather condition (e.g., wind speed and solar radiation), which are shown in Fig. 2. Moreover, as presented in Fig. 3 and Table 1, wind and solar power output could partly match the peak hours' load demand during the whole planning horizon. With regard to the night load peak, it would be mostly met by coal-fired power and natural gas-fired power. For example, at 20:00, the amount of coal-fired power, natural gas-fired power, wind and solar power generation would be [1.323, 1.398], 0.700, [0.342, 0.375], and 0 GWh under the low demand level, respectively.

Fig. 4 displays the optimized power generation schemes of wind power with different λ levels under scenario 1. As shown in Fig. 4, during 4:00 to 8:00 and 20:00 to 24:00, the amount of wind power generation would be relatively lower. Meanwhile, the major generation of wind power would be during 12:00 to18:00, which would be consistent with the forecasted value of wind power output. Taken the high demand level as an example, when λ is fixed as 0.9, the wind power generation at 4:00,12:00, and 18:00 would

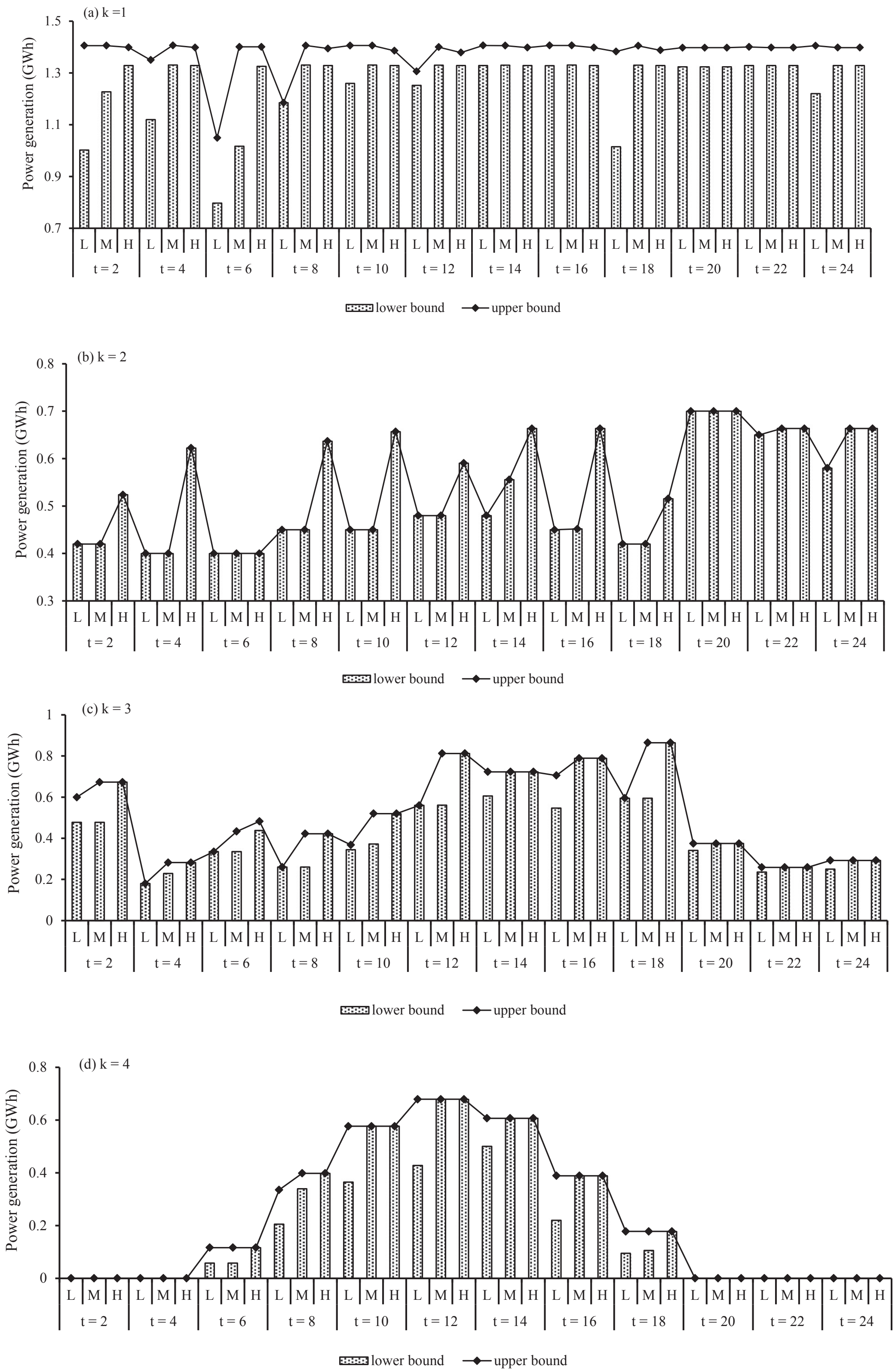

Fig. 3. Optimized power generation with $\lambda = 0.8$ under scenario 1.

be 0.306, [0.863, 0.882], and 0.939 GWh, respectively. In general, as λ values increasing, wind power output would rise up to some extent. For instance, under the low demand level, the wind power generation at 22:00 would be [0.236, 0.238], [0.236, 0.247], [0.236, 0.259], and [0.236, 0.281] GWh, when λ is 0.6 0.7, 0.8, and 0.9, respectively; under the high demand level, it would correspond to 0.238, 0.279, 0.292, and 0.318 GWh, respectively. This could be explained by the reason that as the confidence level λ values

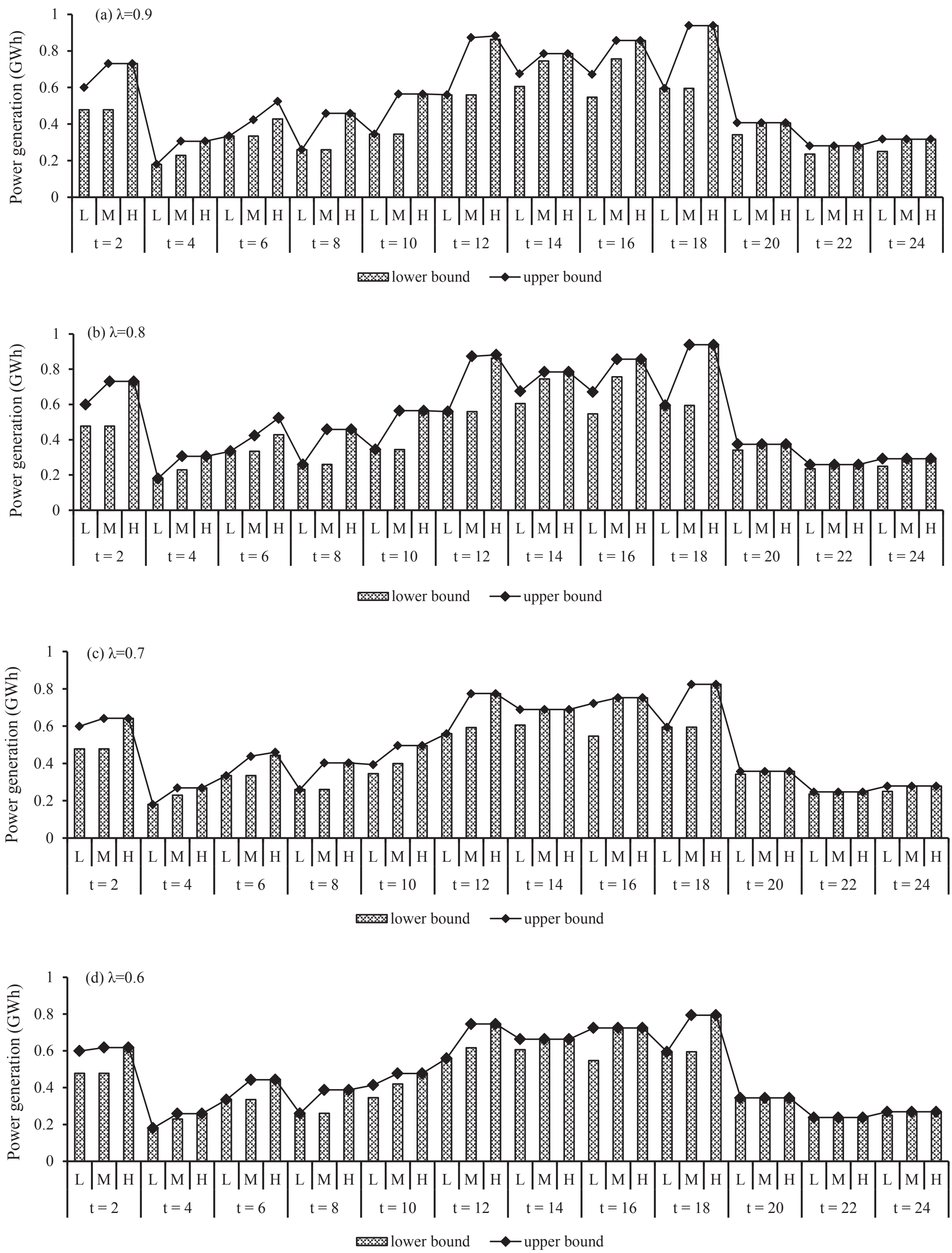

Fig. 4. Optimized wind power generation with different λ levels under scenario 1.

increasing, the availability of wind energy resources related to the coefficient K_λ as mentioned in the proposed model would increase and be sufficient, resulting in the increment of wind power output.

Fig. 5 shows the solutions of conventional conversion technologies generation schemes with λ setting as 0.6 under scenarios 2 and 3. In general, the electricity generation for conventional

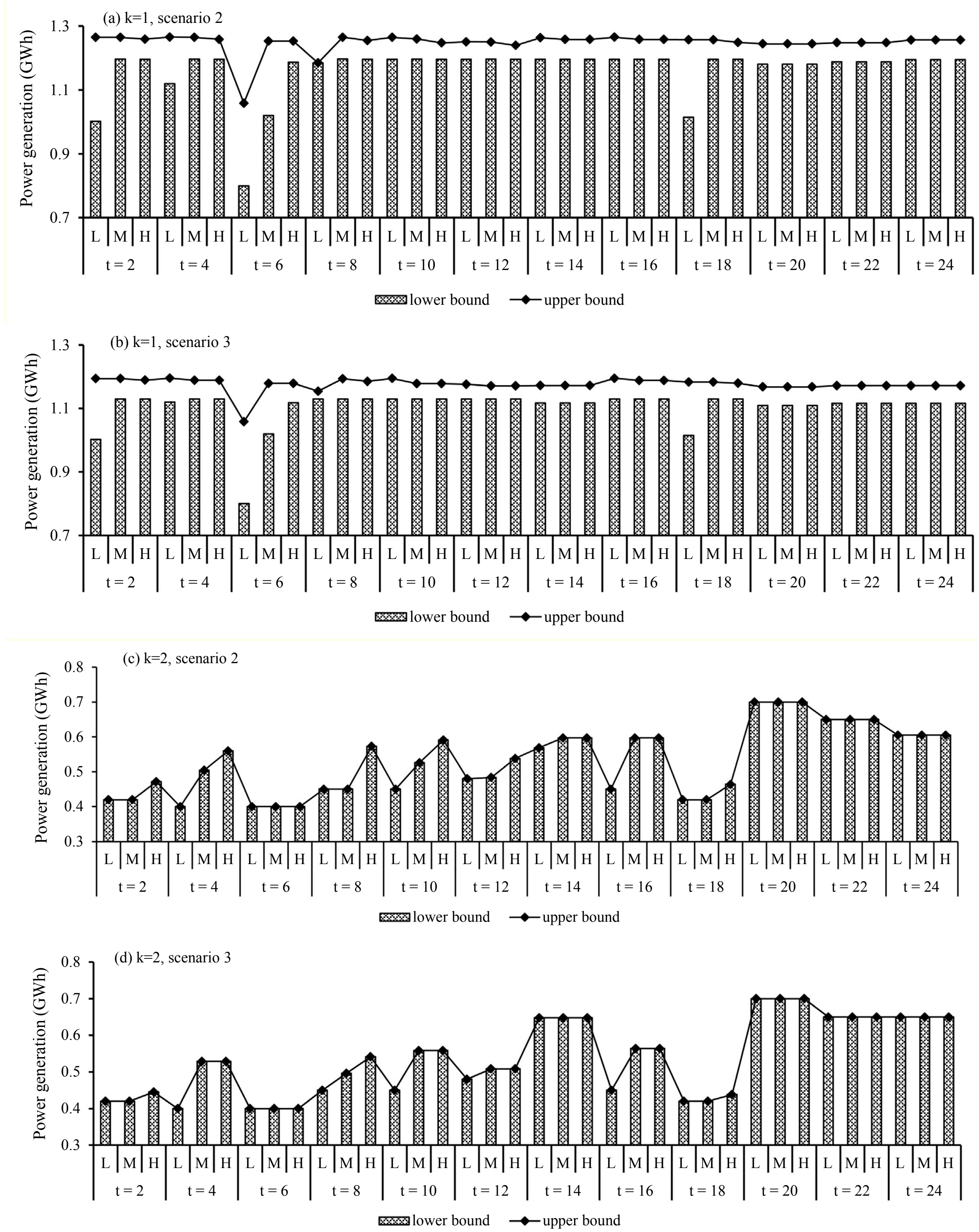

Fig. 5. Traditional generation schemes with $\lambda = 0.6$ under scenarios 2 and 3.

conversion technologies would change as the variation of emission reduction goals. Coal-fired power generation would decrease gradually as the increment of mitigation level under different demand levels. For example, at 8:00, under scenario 2, the coal-fired power generation would be 1.185, [1.197, 1.265], and [1.196, 1.255] GWh under the three demand levels, respectively; under scenario 3, the related coal-fired power generation would be [1.130, 1.154], [1.130, 1.194], and [1.130, 1.185] GWh, respectively. Due to a higher pollutant emission rate, when more strict requirements in environmental standard must be realized, the coal-fired power generation would be reduced. Meanwhile, natural gas-fired power generation would fluctuate as the constraints of environmental protection are added. Taken high demand level as an example, at 10:00, the amount of natural gas-fired power generation would

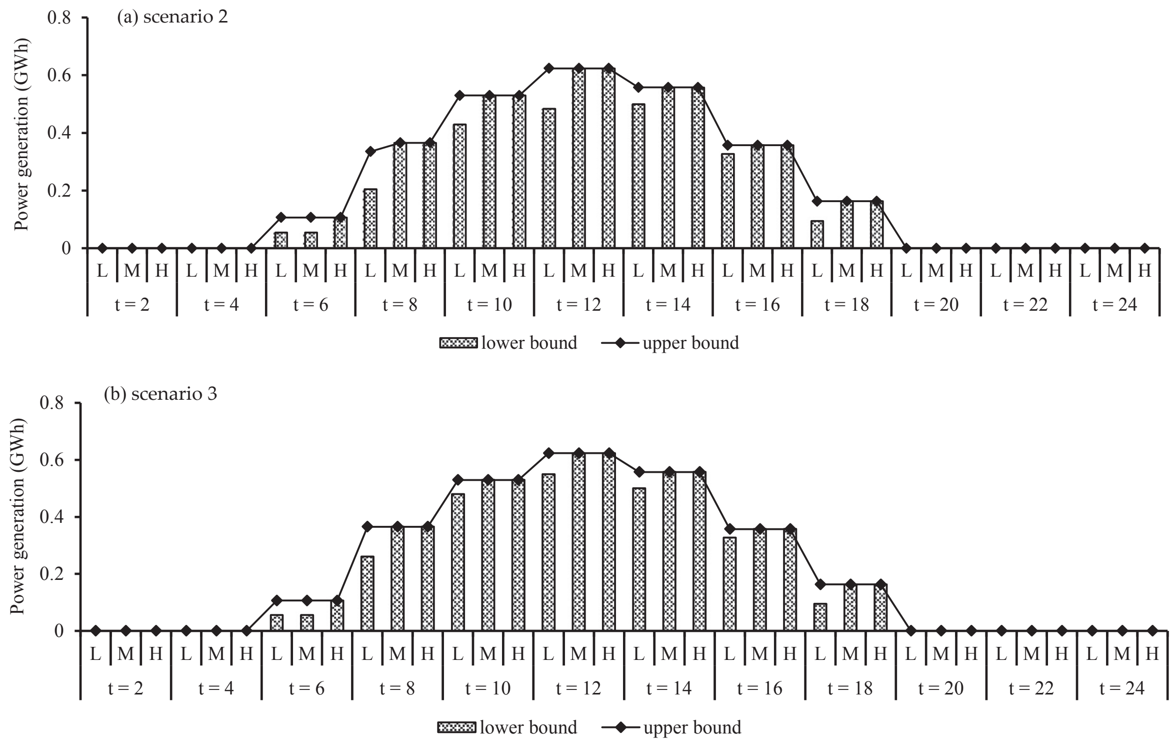

Fig. 6. Output of solar power generation with $\lambda = 0.6$ under scenarios 2 and 3.

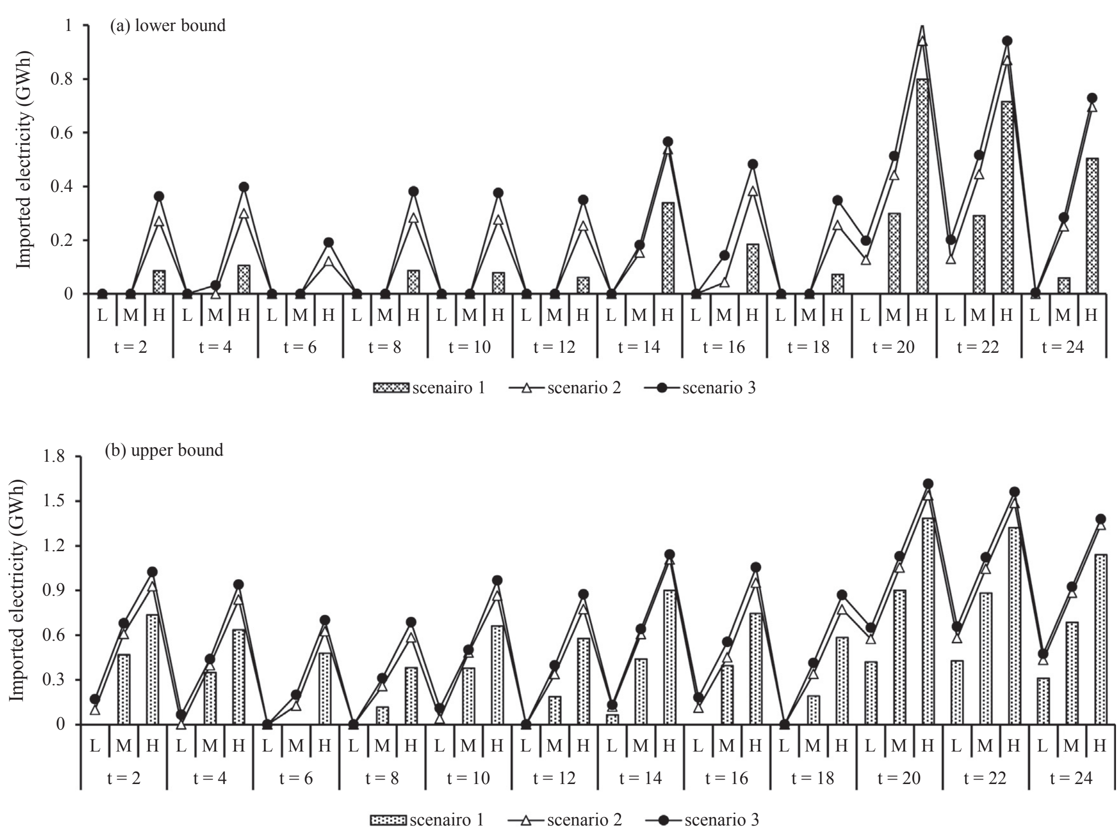

Fig. 7. Optimized amount of imported power with $\lambda = 0.7$ under different scenarios.

decrease, being 0.591 GWh under scenario 2 and 0.558 GWh under scenario 3; while at 14:00, natural gas-fired power generation would increase from 0.597 GWh under scenario 2 to 0.647 GWh under scenario 3.

Fig. 6 presents the output of solar power generation under scenarios 2 and 3 as λ fixed as 0.6 during the planning periods. The maximum output of solar power would be at 12:00 with the value of [0.484, 0.624], 0.624, and 0.624 GWh under low, medium, and high demand level in scenario 2, and [0.55, 0.624], 0.624, and 0.624 GWh in scenario 3, correspondingly. Compared with the conventional power conversion technologies, the renewable energy power generation would increase to a certain degree as the mitigation level increasing. For example, under low demand level, the solar power generation at 8:00 and 10:00 would be [0.205, 0.335] and [0.429, 0.530] GWh under scenario 2, and [0.260, 0.366] and [0.480, 0.530] GWh under scenario 3, respectively. However, the solar power output would be stable when electricity demand levels and environmental requirements reach to a certain level. For instance, at 16:00, solar power generation would be all stabilized at 0.357 GWh for the medium and high demand level with the mitigation level increasing. The main reason is that the solar power generation would reach to its upper generating capacity limitation under scenario 2; therefore, there would be no change with the variation of different environmental objectives. In general, as λ value decreasing, the actual solar power output would be more and more close to its forecasted value. The results simultaneously illustrated that as the conference level decreasing, the failure risk of solar power forecasting would be lessened and the associated system feasibility would be enhanced. If the decision makers possess a risk-averse attitude, a lower λ value would be chosen.

Fig. 7 shows the optimized imported electricity schemes under different scenarios as λ fixed as 0.7. When the total amount of power generation from different power conversion technologies cannot meet the load demand in the region, it would be necessary to import electricity from the main grid. Generally, with the increasing demand level, imported electricity would be employed, reflecting a significant increasing tendency. For example, at 14:00, under scenario 1, the imported electricity amount would be [0, 0.065], [0, 0.439], and [0.339, 0.900] GWh for the three levels, respectively. In addition, imported electricity would increase significantly coupled with the improvement of mitigation level in each demand level. Taken high demand level as an example, at 2:00, the amount of imported electricity would be [0.085, 0.735], [0.270, 0.928], and [0.363, 1.023] GWh under scenario 1 to 3, which would be mainly attributed to the drop of conventional energy power generation confined with a certain level as the improvement of environmental requirements. As

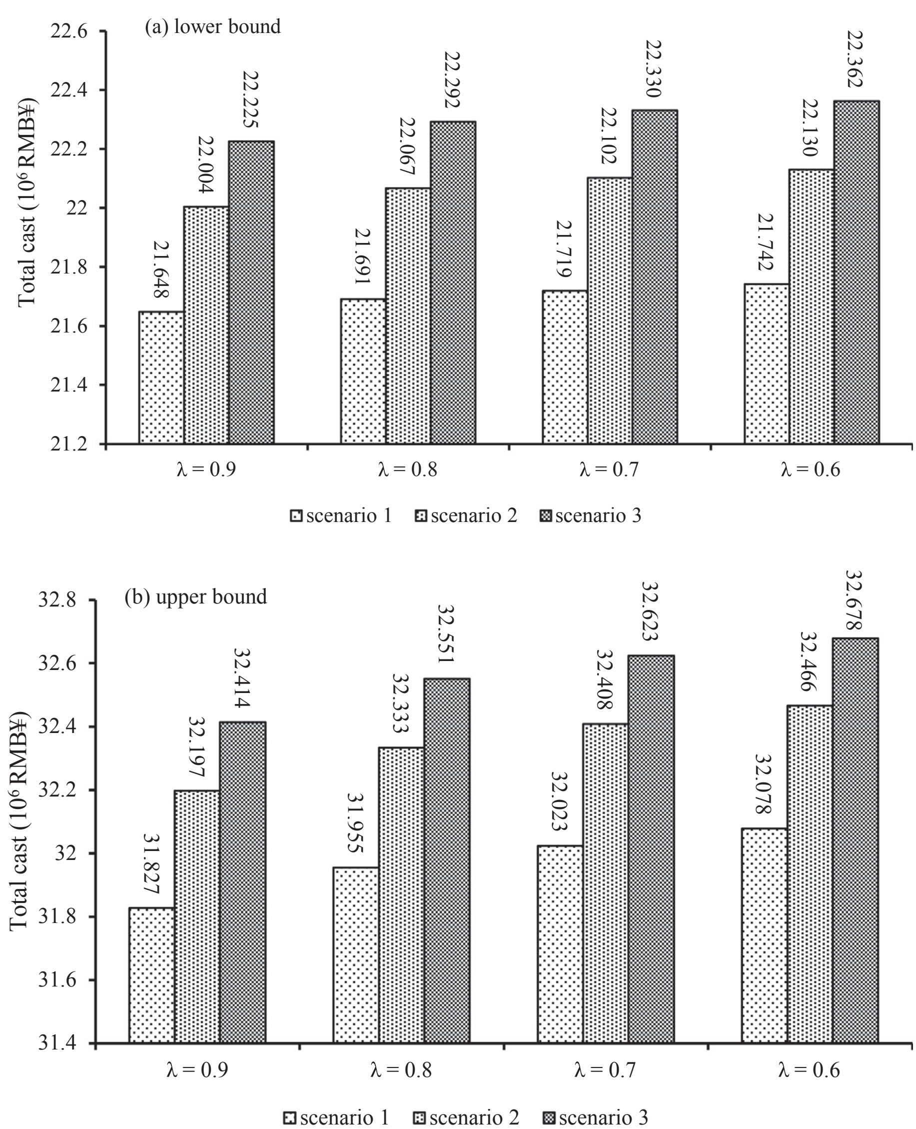

Fig. 8. System cost under different λ and scenarios.

displayed in Fig. 7, during 20:00 to 24:00, imported electricity amount would be relatively higher; and this mostly might be due to the insufficient of renewable power generation.

The expected system cost with different confidence levels under three scenarios is shown in Fig. 8. The results demonstrated that the objective function value would rise up slightly as the confidence level decreasing. For example, under scenario 1, the expected system cost would be RMB¥ [21.648, 31.827] $\times$ 10^6, RMB¥ [21.691, 31.955] $\times$ 10^6, RMB¥ [21.719, 32.023] $\times$ 10^6, RMB¥ [21.742, 32.078] $\times$ 10^6 with λ setting as 0.9, 0.8, 0.7, and 0.6, respectively. It is illustrated that there exists a trade-off between system economy and risk in the electric power system management, which should be evaluated by decision makers. In general, a lower λ level meaning a lower availability of renewable energy resources, would result in a lower deviation to the output forecast of renewable energy power as well as a higher system cost; conversely, vice versa. Meanwhile, as the λ decreasing, the system risk would be decreased and system reliability would be improved. In addition, the system cost would increase as the constraints of emission reduction are enforced. For example, when λ is equal to 0.8, the expected system cost would be RMB¥ [21.691, 31.955] $\times$ 10^6, RMB¥ [22.067, 32.333] $\times$ 10^6, and RMB¥ [22.292, 32.551] $\times$ 10^6 under scenario 1 to 3, respectively. It is mainly because that as the mitigation level rising up, the amount of conventional power generation would be reduced; as a result, more imported electricity would be purchased. If the decision makers possess a risk-taker attitude towards a lower system cost, the environmental regulations might be broke. Therefore, the decision makers should make a choice between a lower cost related to a more optimistic and flexible scheme and a higher cost corresponding to a more conservative and reliable plan.

The study problem can be solved through an interval two-stage stochastic programming method (ITSP) as well if the model would not take the fluctuation of power output into consideration and the constraints should be totally satisfied (i.e. $\lambda = 1$). The objective function solutions of ITSP is RMB¥ [21.783, 33.274] $\times$ 10^6, which is higher than that of ITSFP. The result demonstrated that the manager would choose a lower system risk and more conservative generation scheduling. Compared with the single results of ITSP, it is indicated that the ITSFP method can provide multiple decision alternatives for decision makers. In the process of power dispatch, the decision makers can choose the confidence level according to the actual situation and their willingness, and obtain different decision making combining the system economy and risk. Furthermore, the ITSFP has advantages over the ITSP in sufficiently reflecting the fuzziness of power output and consider power forecast errors.

5. Conclusion

In this study, an inexact two-stage stochastic fuzzy programming model was developed for regional electric power system management under uncertainty. The proposed model was formulated through incorporating two-stage stochastic programming, and fuzzy credibility constrained programming into a general interval-parameter programming optimization framework. It can address multiple formats of uncertainties expressed as intervals, probability distributions, and fuzzy sets in both objective function and system constraints. The model is effective in providing a linkage between pre-regulated electric power generation schedule and the relevant economic implications, and generating more reasonable decision alternatives that would be helpful for decision makers to deal with various system conditions when considering economic and environmental policies. Besides, the notion of fuzzy risk can be sufficiently represented by the fuzzy credibility index. Particularly, based on this method, the fuzziness of forecast error could be effectively reflected through introducing the crisp equivalent equation of fuzzy chance constraints.

The performance of the developed method was then applied to a case of short-term regional electric power generation scheduling considering the fluctuant real-time renewable energy output and air pollutant control. Three scenarios related to different pollutants emission control policies and several credibility levels corresponding to decision makers' willingness were considered. The power generation schemes, imported electricity, as well as system cost were analyzed. The obtained results indicated that the proposed model could effectively capture the variability of renewable energy and permit in-depth analyses for the trade-off between economic objective and system risk under different confidence levels. The actual output of renewable energy technology would be closer to the forecasted values with the decrease of confidence levels. The lower confidence level with respect to the lower availability of renewable energy resources would lead to a higher system cost and a lower risk of violating the system security. Meanwhile, the lower mitigation level of total emission permit, the lower system cost. The results are valuable for managers to make a compromise among the economic cost, environmental requirements, and system risk.

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Appendix A. Solution method

Based on an interactive algorithm [39], model (5) can be transformed into two deterministic submodels corresponding to the lower and upper bounds of the desired objective-function value, respectively. Because the objective is to minimize system cost, the submodel for f^- corresponding to the lower-bound objective-function can be firstly formulated as follows:

$$\min\ f^- = \sum_{j=1}^{k_1} c_j^- \left(x_j^- + \mu_j \Delta x_j\right) + \sum_{h=1}^{s} p_h \left(\sum_{j=1}^{k_2} d_j^- y_{jh}^- + \sum_{j=k_2+1}^{n_2} d_j^- y_{jh}^+ \right) \tag{A.1a}$$

subject to:

$$\sum_{j=1}^{k_1} |a_{rj}|^+ \mathrm{sign}\left(a_{rj}^+\right)\left(x_j^- + \mu_j \Delta x_j\right) \le b_r^{'-} + b_r^{'-} |E_{w-}| \sqrt{\frac{2\lambda_r^+ - 1}{2\sigma_r\left(1-\lambda_r^+\right)}},\ \forall r \tag{A.1b}$$

$$\sum_{j=1}^{k_1} |a_{rj}|^+ \mathrm{sign}\left(a_{rj}^+\right)\left(x_j^- + \mu_j \Delta x_j\right) + \sum_{j=1}^{k_2} \left|a_{ij}^{'}\right|^+ \mathrm{sign}\left(a_{ij}^{'}\right) y_{jh}^- + \sum_{j=k_2+1}^{n_2} \left|a_{ij}^{'}\right|^- \mathrm{sign}\left(a_{ij}^{'-}\right) y_{jh}^+ \ge \tilde{w}_{ih}^-, \quad \forall i,h \tag{A.1c}$$

$$x_j^- + \mu_j \Delta x_j \geq 0, \quad j = 1, 2, ..., k_1 \tag{A.1d}$$

$$y_{jh}^- \geq 0, \; j = 1, 2, ..., n_2 \tag{A.1e}$$

$$y_{jh}^+ \geq 0, \; j = k_2 + 1, k_2 + 2, ..., n_2 \tag{A.1f}$$

where μ_j, y_{jh}^- and y_{jh}^+ are decision variables; y_{jh}^-, $j = 1, 2, ..., k_2$ and $h = 1, 2, ..., s$ are random variables with positive coefficients in the objective function; $y_{jh}^+, j = k_2 + 1, k_2 + 2, ..., n_2$ and $h = 1, 2, ..., s$ are random variables with negative coefficients. Solutions of $y_{jh\,\text{opt}}^-(j = 1, 2, ..., k_2)$, $y_{jh\,\text{opt}}^+(j = k_2 + 1, k_2 + 2, ..., n_2)$ and μ_{jopt} can be obtained through submodel (A.1). The optimized first-stage variables are $x_{jopt} = x_j^- + \mu_{jopt}\Delta x_j (j = 1, 2, ..., n_1)$. Based on the above solutions, the submodel for f^+ corresponding to the upper-bound objective-function value is:

$$\min \; f^+ = \sum_{j=1}^{k_1} c_j^+ x_{jopt} + \sum_{h=1}^{s} p_h \left(\sum_{j=1}^{k_2} d_j^+ y_{jh}^+ + \sum_{j=k_2+1}^{n_2} d_j^+ y_{jh}^- \right) \tag{A.2a}$$

subject to:

$$\sum_{j=1}^{k_1} |a_{ij}|^- \text{sign}\left(a_{rj}^-\right) x_{jopt} \leq b_r'^+ + b_r'^+ |E_{w-}| \sqrt{\frac{2\lambda_r^- - 1}{2\sigma_r \left(1 - \lambda_r^-\right)}}, \quad \forall r \tag{A.2b}$$

$$\begin{aligned} &\sum_{j=1}^{k_1} |a_{rj}|^- \text{sign}\left(a_{rj}^-\right) x_{jopt} + \sum_{j=1}^{k_2} \left|a_{ij}^{'}\right|^- \text{sign}\left(a_{ij}^{'-}\right) y_{jh}^+ \\ &\quad + \sum_{j=k_2+1}^{n_2} \left|a_{ij}^{'}\right|^+ \text{sign}\left(a_{ij}^{'+}\right) y_{jh}^- \geq \tilde{w}_{ih}^+, \quad \forall i, h \end{aligned} \tag{A.2c}$$

$$y_{jh}^+ \geq y_{jhopt}^-, j = 1, 2, ..., k_2, \forall h \tag{A.2d}$$

$$y_{jhopt}^+ \geq y_{jh}^-, \; j = k_2 + 1, k_2 + 2, ..., n_2, \quad \forall h \tag{A.2e}$$

Solutions of $y_{jh\,\text{opt}}^+(j = 1, 2, ..., k_2)$ and $y_{jh\,\text{opt}}^-(j = k_2 + 1, k_2 + 2, ..., n_2)$ can be obtained through submodel (A.2). Thus, we can obtain the interval solutions for model as follows:

$$x_{jopt} = x_j^- + \mu_{jopt}\Delta x_j, \quad \forall j \tag{A.3a}$$

$$y_{khopt}^{\pm} = \left[y_{khopt}^-, y_{khopt}^+\right], \quad \forall j, h \tag{A.3b}$$

$$f_{opt}^{\pm} = \left[f_{j\,opt}^-, f_{j\,opt}^+\right] \tag{A.3c}$$

Appendix B. Nomenclatures for parameters and variables

k	type of electricity conversion technologies, $k = 1$ for coal-fired power, $k = 2$ for natural gas-fired power, $k = 3$ for wind power, $k = 4$ for solar power
h	the power load demand level, $h = 1$ for low demand level, $h = 2$ for medium demand level, $h = 3$ for high demand level
r	type of pollutant, $r = 1$ for SO_2, $r = 2$ for NO_X, $r = 3$ for particulate matter (PM)
t	planning period, $t = 1, 2, ..., 24$

Decision variables

$X_{kt}^{\pm}$	predefined electricity generation by technology k in period t (GWh)
$Q_{kth}^{\pm}$	excess electricity generation by technology k in scenario h during period t(GWh)
$IP_{th}^{\pm}$	amount of imported power in scenario h during period t (GWh)

Parameters

$EC_{kt}^{\pm}$	energy price for technology k in period t (RMB¥10^3/PJ)
$PV_{kt}^{\pm}$	operation cost of technology k for pre-regulated electricity generation in period t (RMB¥10^3/GWh)
$PP_{kt}^{\pm}$	operation cost of technology k for excess electricity generation in period t(RMB¥10^3/GWh)
p_{th}	probability of occurrence for scenario h in period t
$IE_t^{\pm}$	power purchase price (RMB¥10^3/GWh)
$CE_{krt}^{\pm}$	removal cost of pollutant r from technology k in period t (RMB¥10^3/tonne)
$PE_{krt}^{\pm}$	penalty cost of excess pollutant r from technology k in period t(RMB¥10^3/tonne)
$EF_{krt}^{\pm}$	emission intensity of pollutant r from power generation technology k in period t (tonne/GWh)
$UPC_t^{\pm}$	coal energy resource limit in period t (PJ)
$UPN_t^{\pm}$	natural gas energy resource limit in period t (PJ)
$PW_t^{'}$	wind power output forecast during period t (GW)
$SW_t^{'}$	solar power output forecast during period t (GW)
ξ_w	percentage error of wind power in forecast
ξ_s	percentage error of solar power in forecast
$\lambda^{\pm}$	the confidence level
$DM_{th}^{\pm}$	the hourly load demand in scenario h during period t (GWh)
$\eta_{krt}^{\pm}$	average removal efficiency of pollutant r for power conversion technology k in period t
$CG_{kt}^{\pm}$	the conversion efficiency of power generation technology k in period t (PJ/GWh)
RC_k	residual capacity for power conversion technology k (GW)
$ST_{kt}^{\pm}$	operation time of power generation technology k in period t (h)
$ES_{rt}^{\pm}$	allowance amount of pollutant r emission in period t (tonne)

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