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Planning of Electric Power Generation Systems under Multiple Uncertainties and Constraint-Violation Levels

Q. Hu[1,2], G. H. Huang[1,*], Y. P. Cai[3,4,*], and W. Sun[4]

[1]*MOE Key Laboratory of Regional Energy Systems Optimization, Resources and Environmental Research Academy, North China Electric Power University, Beijing 102206, China*
[2]*Beijing Building Technology Development Co. Ltd, 1 Guanglian Road, Xicheng Dstrict, Beijing 100055, China*
[3]*State Key Laboratory of Water Environment Simulation, School of Environment, Beijing Normal University, Beijing 100875, China*
[4]*Institute for Energy, Environment and Sustainable, Communities, University of Regina, Regina, Saskatchewan S4S 7H9, Canada*

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ABSTRACT. Regional electric power generation systems (REPGS) planning involves multiple sectors, multiple facilities, and multiple uncertainties, leading a variety of complexities. In this study, lower-side attainment degrees based inexact fuzzy chance-constraint programming (LA-IFCCP) was proposed to support the planning of REPGS under such a complex situation. LA-IFCCP was developed by integrating lower-side attainment degrees based fuzzy programming (LA-FLP) into an interval chance-constraint programming (ICCP) framework. It was able to tackle uncertainties expressed as intervals, fuzzy sets, probabilistic distributions as well as their combinations. At the same time, fuzzy relationships between conversion efficiencies of technologies and availabilities of energy resources could be transformed into corresponding deterministic ones via the lower-side attainment degree index without introducing any additional constraints, and thus guaranteed enhanced computation efficiency. Moreover, constraint-violation levels about renewable energy resource availabilities could be quantified through the adoption of various pi levels, which could represent the reliability of the system. The relationships between systems costs and reliability could be reflected via analyzing the solutions under different pi levels, which was very important for the management of power generation. A hypothetical but representative regional electric power generation system was adopted for demonstrating its applicability. Reasonable solutions were generated. They provided desired plans regarding energy supply, electricity generation, capacity expansion and emission mitigation to achieve a minimized system cost.

Keywords: electric power generation system, emission mitigation, lower-side attainment degree, constraint-violation, multiple system uncertainties

1. Introduction

Power generation planning is an effective tool for the development of safe, economical and environmentally-friendly energy systems at multiple scales (Mavrotas et al., 2008). In the past decades, soaring electricity demands, increasing environmental concerns, as well as shrinking energy reserves have forced decision makers in many regions to contemplate and propose comprehensive electric power generation plans (Cai et al., 2009a, c). However, in a regional electric power generation system (REPGS), many complex processes should be considered, including energy allocation, conversion and transmission, as well as the associated environmental and social issues (Cai et al., 2009d; Li et al., 2010). Moreover, many system parameters such as electricity demands, energy availabilities, and technology efficiencies may appear uncertain, further complicating the complexities in relevant decision-making processes. Thus, it is desired to develop an effective approach for supporting the planning of regional electric power generation systems under multiple uncertainties.

Previously, a number of inexact optimization techniques were developed to tackle uncertainties and complexities in energy systems planning problems (Sadeghi and Hosseini, 2006; Jana and Chattopadhyay, 2004; Carrión et al., 2007; Weber et al., 2009; Guo et al., 2012, Shen et al., 2012). Among them, inexact chance-constraint programming (ICCP) was an effective approach for addressing uncertainties in the objective function and constraints of an optimization system that can be expressed as intervals. At the same time, it could deal with uncertainties in the right-hand side of the system constraints presented as probabilistic distributions (Cai et al., 2009c). More recently, many studies of ICCP were conducted for tackling energy systems planning problems (Cai et al., 2009b; Liu et al., 2009; Huang et al., 2011). In these studies, ICCP could (a) incorporate dual uncertainties within the corresponding optimi-

* Corresponding author. Tel.: +86 10 61772018; fax: + 86 10 51971284.
E-mail address: huang@iseis.org (G. H. Huang), yanpeng.cai@bnu.edu.cn (Y. P. Cai).

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zation processes, (b) identify decision alternatives under different significance levels, representing at which the constraints would be violated (Huang 1998), and (c) reflect tradeoffs between economic cost and system reliability (Tan et al., 2010a). However, ICCP would encounter difficulties in handling uncertainties expressed as fuzzy sets or combinations of fuzzy sets and interval numbers that were embedded within an individual parameter. Comparatively, a number of fuzzy programming approaches were developed for handling uncertainties expressed as fuzzy sets (Gjorgiev and Cepin, 2013; Hu et al., 2011; Tan et al., 2010b, c; Gjorgiev et al., 2010). For example, Van Hop (2007) adopted the lower-side attainment degrees to deal with fuzzy sets in optimization problems and thus proposed a fuzzy linear programming method (LA-FLP). It could directly reflect the relationships among fuzzy coefficients through the adoption of the lower-side attainment degrees, instead of discrete intervals under varying α-cut levels. Compared with conventional fuzzy programming approaches, efficient computation process could be obtained. Also, the satisfaction or violation degrees about the constraints with fuzzy coefficients could be quantified via the corresponding lower-side attainment values. Although this method has strength in computational efficiency and uncertainty reflection, it could hardly address uncertainties expressed as intervals and probabilistic distributions.

Therefore, the objective of this study is to incorporate the ICCP and LA-FLP methods within a general REPGS model framework, leading to lower-side attainment degrees based inexact fuzzy chance-constraint programming (LA-IFCCP) for REPGS planning. The method can address uncertainties expressed as intervals, fuzzy sets, probabilistic distributions as well as their combinations in the process of REPGS planning. At the same time, it can reflect the tradeoffs between system costs and reliability through analyzing solutions under different constraint-violation levels. A case study will then be provided for demonstrating applicability of the developed method. The results can help decision makers identify desired plans regarding energy allocation, electricity generation, facilities capacity-expansion and emission mitigation under minimized economic costs with consideration of system reliability.

2. Modeling Formulation

2.1. Development of an Inexact Chance-Constraint Programming Model

Consider a regional electric power generation system wherein a decision maker is responsible for assigning electricity generation plans for conversion facilities with consideration of the varied electricity demands and environment requirements in the region. Four types of electricity conversion facilities are considered, including coal-fired and natural gas-fired plants, hydropower station, and wind power farm. For each conversion facility, possible expansion options would be allowed when the residual capacity could not meet requirements of electricity demands. However, the availabilities of primary energy resources (e.g., coal and natural gas) are limited. The decision maker can formulate the problem as minimizing the total system cost with optimal primary energy resources (fossil fuels) allocation patterns, capacity expansion schemes, electricity generation and pollutant mitigation plans.

In this process, many system parameters such as fossil fuel prices and electricity demands are hard to be obtained as deterministic numbers due to insufficient data accumulation. Instead, the decision maker may be confident to present them as intervals or probabilistic distributions. For example, the price of domestic coal is greatly affected by economic and technological issues and is highly uncertain. In order to acquire the values for the parameters related to economic issues, the decision maker may describe “the estimated price of domestic coal in this region would be [2.67, 2.87] $\times 10^3$ \$/TJ”. This represents that the minimum and maximum prices for domestic coal would be 2.67×10^3 \$/TJ and 2.87×10^3 \$/TJ in the study region, respectively, leading to the uncertainty that can be expressed an interval number. Such an interval number $a^\pm$ can be expressed as $[a^-, a^\pm]$, meaning a number having a minimum value of a^- and a maximum value of a^+. Moreover, the availabilities of renewable energy resources (e.g., hydropower and wind power) are fluctuated with the natural and meteorological conditions and can inherently be expressed as probability density functions (Khan and Iqbal, 2005). In order to tackle such multiple formats of uncertainties in electric power generation systems, interval linear programming (ILP) and chance-constraint programming (CCP) methods are incorporated within a general REPGS planning model, leading to an inexact chance-constraint programming model (ICCP). Based on Huang (1998) and Cai et al. (2009b), an ICCP model for regional electric power generation system planning can be formulated as follows:

$$\text{Min}\, f^\pm = \sum_{i=1}^{I}\sum_{t=1}^{T} PRC_{it}^\pm \cdot Z_{it}^\pm + \sum_{t=1}^{T} PIE_t^\pm \cdot ZIE_t^\pm + \sum_{j=1}^{J}\sum_{t=1}^{T} PE_{jt}^\pm \cdot W_{jt}^\pm + \sum_{j=1}^{J}\sum_{t=1}^{T} B_{jt}^\pm \cdot X_{jt}^\pm + \sum_{t=1}^{T} CS_t^\pm \cdot XS_t^\pm + \sum_{t=1}^{T} CN_t^\pm \cdot XN_t^\pm \tag{1a}$$

Subject to:

Mass balance of fossil fuels

$$W_{1t}^\pm \cdot FE_{1t}^\pm \le Z_{1t}^\pm,\ \forall t \tag{1b}$$

$$W_{2t}^\pm \cdot FE_{2t}^\pm \le Z_{2t}^\pm,\ \forall t \tag{1c}$$

Availabilities of energy resources constraints

$$Z_{1t}^\pm \le AVC_t^\pm,\ \forall t \tag{1d}$$

$$Z_{2t}^\pm \le AVG_t^\pm,\ \forall t \tag{1e}$$

$$W_{3t}^\pm \cdot FE_{3t}^\pm \le AVH_t^{pi\pm},\ \forall t \tag{1f}$$

$$W_{4t}^\pm \cdot FE_{4t}^\pm \le AVW_t^{pi\pm},\ \forall t \tag{1g}$$

Electricity demands constraints

$$\sum_{j=1}^{J}(W_{jt}^{\pm} + ZIE_{t}^{\pm}) \geq d_{t}^{\pm},\ \forall t \quad (1h)$$

Capacity constraints for conversion facilities

$$W_{jt}^{\pm} - \sum_{t'=1}^{t} X_{jt}^{\pm} \cdot ST_{jt}^{\pm} \leq RC_{j} \cdot ST_{jt}^{\pm},\ \forall j;\ t \quad (1i)$$

Constraints for capacity expansions

$$X_{jt}^{\pm} \leq M_{jt},\ \forall j;\ t \quad (1j)$$

Air pollution control constraints

$$XS_{t}^{\pm} = \sum_{j=1}^{2} W_{jt}^{\pm} \cdot INS_{jt}^{\pm},\ j = 1,2;\ \forall t \quad (1k)$$

$$XN_{t}^{\pm} = \sum_{j=1}^{2} W_{jt}^{\pm} \cdot INN_{jt}^{\pm},\ j = 1,2;\ \forall t \quad (1l)$$

$$(1-\eta_{st}^{\pm}) \cdot XS_{t}^{\pm} \leq ES_{t}^{\pm},\ \forall t \quad (1m)$$

$$(1-\eta_{nt}^{\pm}) \cdot XN_{t}^{\pm} \leq EN_{t}^{\pm},\ \forall t \quad (1n)$$

Non-negative constraints

$$Z_{it}^{\pm},\ ZIE_{t}^{\pm},\ W_{jt}^{\pm}, XS_{jt}^{\pm}, XN_{jt}^{\pm} \geq 0,\ \forall j;\ t \quad (1o)$$

where f: expected system costs (\$$10^6$); i: fossil fuels; j: conversion facilities; t: periods; pi denotes a series of probability levels, representing the violations of the constraints about renewable energy resources availabilities; $PRC_{it}^{\pm}$: average cost for energy supply i in period t (\$$10^3$/TJ); $PIE_{jt}^{\pm}$: average cost for imported electricity in period t (\$$10^3$/GWh); $PE_{jt}^{\pm}$: operating cost for power conversion facility j in period t (\$$10^3$/GWh); $B_{jt}^{\pm}$: variable cost for capacity expansion of power conversion facility j in period t (\$$10^6$/GW); $CS_{t}^{\pm}$: operating cost for SO_2 mitigation in period t (\$/tonne); $CN_{t}^{\pm}$: operating cost for NO_X mitigation in period t (\$/tonne); $FE_{jt}^{\pm}$: units of energy carrier per unit of electricity production for power conversion facility j in period t (TJ/GWh); $AVC_{t}^{\pm}$: available coal supply during period t (10^3TJ); $AVG_{t}^{\pm}$: available natural gas supply during period t (10^3TJ); $AVH_{t}^{pi\pm}$: availability of hydro power during period t under pi level (10^3TJ); $AVW_{t}^{pi\pm}$: availability of wind power during period t under pi level (10^3 TJ); $d_{t}^{\pm}$: total electricity demand during period t (10^3 GWh); $ST_{jt}^{\pm}$: Average operation hours for conversion facility j in period t (10^3 h)); $RC_{j}^{\pm}$: residual capacity for conversion facility j (GW); M_{jt}: upper bounds for capacity expansion of conversion facility j during period t (GW); $INS_{jt}^{\pm}$: units of SO_2 emission per unit of electricity production for power conversion facility j during period t (tonnes/GWh); $INN_{jt}^{\pm}$: units of NO_X emission per unit of electricity production for power conversion facility j during period t (tonnes/GWh); η_{st}: average efficiency for SO_2 mitigation during period t (%); η_{nt}: average efficiency for NO_X mitigation during period t (%); $ES_{t}^{\pm}$: maximum allowable SO_2 emission during period t (tonnes); $EN_{t}^{\pm}$: maximum allowable NO_X emission during period t (tonnes). The decision variables are: $Z_{it}^{\pm}$: fossil fuel supply during period t (10^3TJ); $ZIE_{t}^{\pm}$: imported electricity during period t (10^3GWh); $W_{jt}^{\pm}$: electricity generation target for conversion facility j during period t (10^3 GWh); $X_{jt}^{\pm}$: variables about capacity expansion of conversion facility j in period t (GW); $XS_{t}^{\pm}$: amount of treated SO_2 in period t (tonnes); $XN_{t}^{\pm}$: amount of treated NO_X in period t (tones).

Obviously, the objective of the proposed ICCP model is to minimize the total system costs, which consists of five parts: costs for fossil fuel supplies, imported electricity, capacity expansion, electricity generation and pollutant mitigation. Plans regarding fossil fuel supplies, capacity expansion, electricity generation and pollutant mitigation can be generated by solving ICCP. Also, uncertainties expressed as intervals and probabilistic distributions can be integrated into the process of modelling formulation, and solution calculation, which improves the robustness of the results. Furthermore, the violation of constraints about renewable energy resources availabilities can be quantified by pi levels, which is very important for security analysis of power generation plans. However, there are still shortcomings in the proposed ICCP model. For example, it is ineffective for uncertainties expressed as fuzzy sets and multiple uncertainties embedded within an individual parameter.

2.2. Development of a Lower-Side Attainment Degrees Based Fuzzy Linear Programming Model

Let $\tilde{T}$ be a family of triangular fuzzy numbers. According to Zimmerman (2001), it can be defined as follows:

$T = \{\tilde{t},\ \tilde{t} = (t, l, r), l, r \geq 0\}$, and

$$\mu_{\tilde{t}}(x) = \begin{cases} \max(0, 1-(t-x)/l), & if\ x \leq t \\ 1 & if\ l=0, r=0, t=x \\ \max(0, 1-(x-t)/r), & if\ x \geq t \\ 0 & otherwise \end{cases} \quad (2)$$

where the scalars $l, r \geq 0$ ($l, r \in R$) are named left and right spreads, respectively. Based on the definition, a new method is proposed to compare two fuzzy numbers through lower-side attainment degrees.

Given two fuzzy numbers $\tilde{U}(u,a,b)$, $\tilde{V}(v,c,d)$ and $\tilde{U} \leq \tilde{V}$, according to Van Hop (2007), when the intersection between the right side of $\tilde{U}(u,a,b)$ and the left side of $\tilde{V}(v,c,d)$ exists, the lower-side attainment degree of $\tilde{U}$ to $\tilde{V}$ can be defined as follows (at an α-cut level, attainment degree of fuzzy number $\tilde{U}$ to $\tilde{V}$ is displayed in Figure 1):

$$D(\tilde{U}, \tilde{V}) = \int_0^1 \max\{0, \sup\{s \in R : \tilde{U}(s) \geq \alpha\} - \inf\{r \in R : \tilde{V}(r) \geq \alpha\}\} d\alpha \quad (3)$$

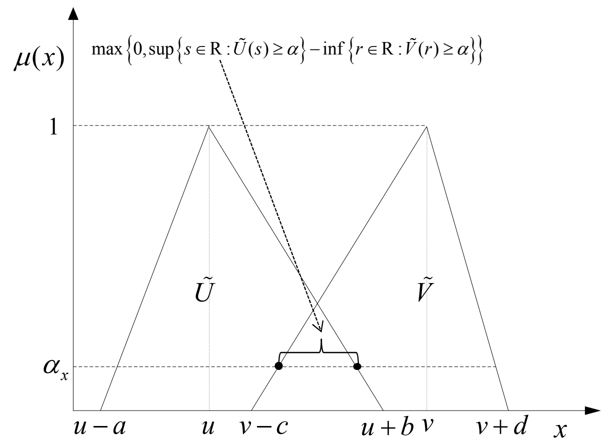

Figure 1. Attainment degree of fuzzy number $\tilde{U}$ to $\tilde{V}$ at α-level.

The both-side attainment degree of fuzzy number $\tilde{U}$ to $\tilde{V}$ can be defined as follows:

$$G(\tilde{U},\tilde{V}) = \max\{0, \min(D(\tilde{U},\tilde{V}), D(\tilde{U},\tilde{V}))\} \tag{4}$$

The average lower-side attainment degree of $\tilde{U}$ to $\tilde{V}$ can be obtained as:

$$\overline{D}(\tilde{U},\tilde{V}) = (u - v + b + c)/2 \tag{5}$$

When the intersection does not exist, $\overline{D}(\tilde{U},\tilde{V})$ equals to zero (Chou et al. 2009). The average lower-side attainment degree index proposed above can effectively transform fuzzy relationships between fuzzy numbers into corresponding deterministic ones and reflect the attainment degree of two fuzzy numbers without any additional constraints. This can be used to solve fuzzy linear programming problems. Consider the following fuzzy linear programming model:

$$Min\ cx \tag{6a}$$

Subject to:

$$\sum_{j=1}^{n}(\tilde{a}_{ij})x_j \leq (\tilde{b}_i); i = 1, 2, \ldots, m \tag{6b}$$

$$x_j \geq 0 \tag{6c}$$

where c is a $1 \times n$ matrix. Applying the lower-side attainment degree index to minimize the achievement of the left-hand side to the right-hand side, model (6) can be de-fuzzified as follows:

$$Min\ cx + \sum_{i=1}^{m}\lambda_i \tag{7a}$$

Subject to:

$$\overline{D_i}\left(\sum_{j=1}^{n}(\tilde{a}_{ij})x_j \leq (\tilde{b}_i)\right) = \lambda_i;\ i = 1, 2, \ldots, m \tag{7b}$$

$$x_j \geq 0 \tag{7c}$$

2.3. Development of a Lower-Side Attainment Degrees Based Inexact Fuzzy Chance-Constraint Programming Model

According to Van Hop (2007), LA-FLP can effectively tackle uncertainties expressed as fuzzy sets. Comparatively, ICCP model is an effective method for dealing with uncertainties existed as interval numbers, probabilistic distributions as well their combination during REPGS planning. However, both of them would be inefficient when multiple uncertainties embedded within an individual parameter. For example, availabilities of renewable energy resources (e.g., hydropower and wind power) may be expressed as fuzzy boundary intervals with known probabilistic distributions. An interval with triangle fuzzy boundaries can be expressed as $[(\delta,\ a,\ b),\ (\theta,\ c,\ d)]$, which means the lower and upper bounds of the interval are triangle fuzzy numbers with the most value being δ and θ, respectively. They also have the variations to the left and right being a and b, c and d for lower and upper bounds, respectively. When the variation to the left and right equals to each other, the above interval can be given as $[(\delta,\ a),\ (\theta,\ c)]$. All the intervals with fuzzy boundaries in this study are given in the same way. In order to handle such multiple uncertainties, a lower-side attainment degrees based inexact fuzzy chance-constraint programming model (LA-IFCCP) is developed through introducing LA-FLP into an inexact chance-constraint programming model for REPGS. Thus, the model can be formulated as follows:

$$Min\ f^{\pm} = \sum_{i=1}^{I}\sum_{t=1}^{T}PRC_{it}^{\pm} \cdot Z_{it}^{\pm} + \sum_{t=1}^{T}PIE_t^{\pm} \cdot ZIE_t^{\pm} + \sum_{j=1}^{J}\sum_{t=1}^{T}PE_{jt}^{\pm} \cdot W_{jt}^{\pm} + \sum_{j=1}^{J}\sum_{t=1}^{T}B_{jt}^{\pm} \cdot X_{jt}^{\pm} + \sum_{t=1}^{T}CS_t^{\pm} \cdot XS_t^{\pm} + \sum_{t=1}^{T}CN_t^{\pm} \cdot XN_t^{\pm} \tag{8a}$$

Subject to:

$$W_{1t}^{\pm} \cdot F\tilde{E}_{1t}^{\pm} \leq Z_{1t}^{\pm},\ \forall t \tag{8b}$$

$$W_{2t}^{\pm} \cdot F\tilde{E}_{2t}^{\pm} \leq Z_{2t}^{\pm},\ \forall t \tag{8c}$$

$$Z_{1t}^{\pm} \leq AV\tilde{C}_t^{\pm},\ \forall t \tag{8d}$$

$$Z_{2t}^{\pm} \leq AV\tilde{G}_t^{\pm},\ \forall t \tag{8e}$$

$$W_{3t}^{\pm} \cdot F\tilde{E}_{3t}^{\pm} \leq AV\tilde{H}_t^{pi\pm},\ \forall t \tag{8f}$$

$$W_{4t}^{\pm} \cdot F\tilde{E}_{4t}^{\pm} \leq AV\tilde{W}_t^{pi\pm},\ \forall t \tag{8g}$$

$$\sum_{j=1}^{J}(W_{jt}^{\pm} + ZIE_t^{\pm}) \geq d_t^{\pm},\ \forall t \tag{8h}$$

$$W_{jt}^{\pm}-\sum_{t'=1}^{t}X_{jt}^{\pm}\cdot ST_{jt}^{\pm}\leq RC_j\cdot ST_{jt}^{\pm},\ \forall j;\ t \tag{8i}$$

$$X_{jt}^{\pm}\leq M_{jt},\ \forall j;\ t \tag{8j}$$

$$XS_t^{\pm}=\sum_{j=1}^{2}W_{jt}^{\pm}\cdot INS_{jt}^{\pm},\ j=1,2;\ \forall t \tag{8k}$$

$$XN_t^{\pm}=\sum_{j=1}^{2}W_{jt}^{\pm}\cdot INN_{jt}^{\pm},\ j=1,2;\ \forall t \tag{8l}$$

$$(1-\eta_{st}^{\pm})\cdot XS_t^{\pm}\leq ES_t^{\pm},\ \forall t \tag{8m}$$

$$(1-\eta_{nt}^{\pm})\cdot XN_t^{\pm}\leq EN_t^{\pm},\ \forall t \tag{8n}$$

$$Z_{it}^{\pm},\ ZIE_t^{\pm},\ W_{jt}^{\pm}, XS_{jt}^{\pm}, XN_{jt}^{\pm}\geq 0,\ \forall j;\ t \tag{8o}$$

where $F\tilde{E}_{jt}^{\pm}$ represent that units of energy carrier per unit of electricity production for power conversion facility j in period t are fuzzy boundary intervals. $AV\tilde{C}_t^{\pm}$ and $AV\tilde{G}_t^{\pm}$ represent that the availabilities of domestic coal and natural-gas during period t are presented as fuzzy boundary intervals. $AV\tilde{H}_t^{pi\pm}$ and $AV\tilde{W}_t^{pi\pm}$ mean that under pi level, the availabilities of hydropower and wind power are expressed as fuzzy boundary intervals.

In order to show the solution method of model (8), model (8) is generalized as follows:

$$Min\ f^{\pm}=C^{\pm}X^{\pm} \tag{9a}$$

Subject to:

$$A_r^{\pm}X_r^{\pm}\leq b_r^{\pm},\ r\in M, r\neq s \tag{9b}$$

$$\tilde{A}_s^{\pm}X_s^{\pm}\leq \tilde{b}_s^{\pm}(t)^{(ps)},\ s\in M, r\neq s \tag{9c}$$

$$X^{\pm}\geq 0 \tag{9d}$$

where $C^{\pm}\in\{R^{\pm}\}^{1\times n}$, $A_r^{\pm}\in\{R^{\pm}\}^{r\times n}$, $b_r^{\pm}\in\{R^{\pm}\}^{r\times 1}$, $\tilde{A}_s^{\pm}\in\{\tilde{R}^{\pm}\}^{s\times n}$, $\tilde{b}_s^{\pm}(t)^{(ps)}\in\{\tilde{R}^{\pm}\}^{s\times 1}$, $M=(1,2,...,m)$, $\tilde{b}_s^{\pm}(t)^{(ps)}$ represents corresponding values given the cumulative distribution of $\tilde{b}_s^{\pm}$ and the probability of violating constraints s, $\tilde{R}^{\pm}$ denotes a set of interval numbers with fuzzy boundaries. $R^{\pm}$ denotes a set of interval numbers with deterministic boundaries.

According to Huang (1998) and Van Hop (2007), model (9) can be solved through the following two submodels. Since the objective is to get the minimum value, the submodel correspondding to f^- is firstly formulated, and then the submodel corresponding to f^+ can be obtained based on the solutions of the first submodel. Consequently, submodel corresponding to f^- can be firstly formulated as follows:

$$Min\ f^{-}=\sum_{j=1}^{k}c_j^{-}x_j^{-}+\sum_{j=k+1}^{n}c_j^{-}x_j^{+}+\sum_{i=1}^{m}\lambda_{1s} \tag{10a}$$

Subject to:

$$\sum_{j=1}^{k}|a_{rj}^{\pm}|^{+}\ sign(a_{rj}^{\pm})x_j^{-}+\sum_{j=k+1}^{n}|a_{rj}^{\pm}|^{-}\ sign(a_{rj}^{\pm})x_j^{+}\leq b_r^{+};\forall r, r\neq s \tag{10b}$$

$$\overline{D_s}\left(\sum_{j=1}^{k}|\tilde{a}_{sj}^{\pm}|^{+}\ sign(\tilde{a}_{sj}^{\pm})x_j^{-}+\sum_{j=k+1}^{n}|\tilde{a}_{sj}^{\pm}|^{-}\ sign(\tilde{a}_{sj}^{\pm})x_j^{+},\tilde{b}_s^{+}(t)^{(ps)}\right)=\lambda_{1s};\ \forall s, s\neq r \tag{10c}$$

$$x_j^{\pm}\geq 0,\ j=1,...,n \tag{10d}$$

where $|a_{rj}|^{-}$ and $|a_{rj}|^{+}$ represent the lower and upper bounds of the absolute value of $a_{rj}^{\pm}$, respectively; sign($a_{rj}^{\pm}$) is the sigh of $a_{rj}^{\pm}$ (i.e., $\text{sign}(a_{rj}^{\pm})=1$ when $a_{rj}^{\pm}\geq 0$; $\text{sign}(a_{rj}^{\pm})=-1$ when $a_{rj}^{\pm}\leq 0$); x_j^{-} (j = *1,2,.., k*) are interval variables with positive coefficients in the objective function, and x_j^{+} (j = k + 1, k + 2, …, n)are interval variables with negative coefficients in the objective function. Solutions of x_{jopt}^{-} (j = 1, 2, .., k) and x_{jopt}^{+} (j = k + 1, k + 2, …, n) can be obtained through solving model (10). Then, the submodel corresponding to f^+ can be formulated as follows:

$$Min\ f^{+}=\sum_{j=1}^{k}c_j^{+}x_j^{+}+\sum_{j=k+1}^{n}c_j^{+}x_j^{-}+\sum_{i=1}^{m}\lambda_{2s} \tag{11a}$$

Subject to:

$$\sum_{j=1}^{k}|a_{rj}^{\pm}|^{-}\ sign(a_{rj}^{\pm})x_j^{+}+\sum_{j=k+1}^{n}|a_{rj}^{\pm}|^{+}\ sign(a_{rj}^{\pm})x_j^{-}\leq b_r^{-}=\lambda_{2r};\ \forall r, r\neq s \tag{11b}$$

$$\overline{D_s}\left(\sum_{j=1}^{k}|\tilde{a}_{sj}^{\pm}|^{-}\ sign(\tilde{a}_{sj}^{\pm})x_j^{+}+\sum_{j=k+1}^{n}|\tilde{a}_{sj}^{\pm}|^{+}\ sign(\tilde{a}_{sj}^{\pm})x_j^{-},\tilde{b}_s^{-}(t)^{(ps)}\right)=\lambda_{2s};\ \forall s, s\neq r \tag{11c}$$

$$x_j^{\pm}\geq 0,\ j=1,...,n \tag{11d}$$

$$x_j^{+}\geq x_{jopt}^{-},\ j=1,2,...,k \tag{11e}$$

$$x_j^{-}\leq x_{jopt}^{+},\ j=k+1,...,n \tag{11f}$$

Hence, solutions of x_{jopt}^{+} (j = 1, 2, .., k) and x_{jopt}^{-} (j = k + 1, k + 2, …, n) can be obtained from submodel (11). The final solutions for model (8) can be obtained by combining the solutions from the two submodels (10) and (11), i.e., $f_{opt}^{\pm}$ = $[f_{opt}^{-}, f_{opt}^{+}]$ and $x_{jopt}^{\pm}=[x_{jopt}^{-}, x_{jopt}^{+}]$.

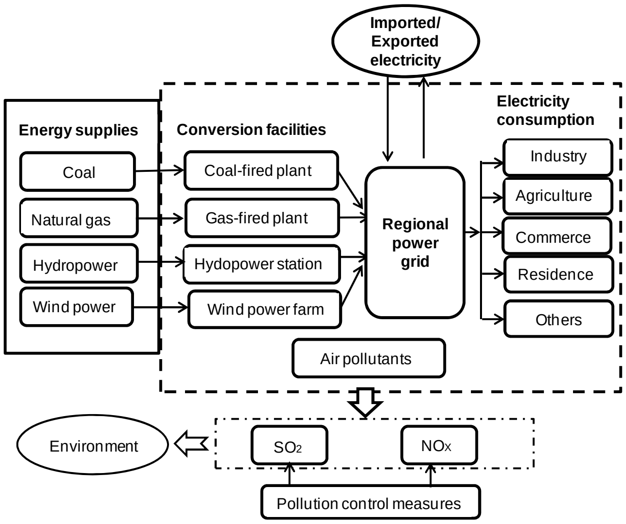

Figure 2. Framework for the case study.

Table 1. Energy Availabilities and Electricity Demands

		Period		
		t = 1	t = 2	t = 3
Energy resources availability (10^3 TJ):				
Coal		(400, 20)*	(380, 20)	(360, 20)
Natural gas		(235, 15)	(270, 15)	(290, 15)
Hydro power	$p_i = 0.01$	(180, 15)	(210, 15)	(220, 15)
	$p_i = 0.05$	(185, 15)	(215, 15)	(225, 15)
	$p_i = 0.1$	(190, 15)	(220, 15)	(230, 15)
Wind power	$p_i = 0.01$	(120, 10)	(125, 10)	(130, 10)
	$p_i = 0.05$	(125, 10)	(130, 10)	(135, 10)
	$p_i = 0.1$	(130, 10)	(135, 10)	(140, 10)
Electricity demand(10^3 GWh)		[66, 80]	[106, 125]	[153,173]

* Represents a triangle fuzzy number, meaning the most possibilistic coal availability in the region being 400 × 10^3 TJ and the variation to the left and right being 20 × 10^3 TJ.

3. Case Study

3.1. Overview of the Study System

A regional-scale electric power generation system (Figure 2) will be analyzed based on information as shown in Li et al. (2009; 2010), Liu et al. (2009) and Cai et al. (2009b,c,d) to demonstrate the applicability of the developed LA-IFCCP model. In the study system, four main sectors are considered, including energy supply, conversion, and demand sectors, as well as the associated environmental issues. The supply sector is to provide raw energies including coal, natural gas, hydropower and wind power to conversion facilities to generate electricity. The conversion sector contains various electricity conversion facilities including coal-fired and natural gas-fired plants, hydropower station and wind power farm with various economic, environmental and technological implications. The demand sector involves multiple end-users that drive energy consumptions and is characterized by varying socio-economic, geographical, demographic, technological and environmental conditions. The environmental protection sector is to regulate energy-related environmental protection policies (Li et al., 2010). These four sectors are interactive with each other. Any changes in one sector would lead to a series of consequences to and responses from the others, resulting in variations in system costs (Cai et al., 2009d). Thus it is necessary to take all the sectors into consideration to reflect overall system characteristics in planning such a system.

The planning horizon covers three periods, with each having a time interval of five years. Residual capacities for each conversion facility at the beginning of the planning horizon are 1.0, 0.35, and 0.30 GW for coal-fired and natural gas-fired plants, and hydropower station, respectively. When the electricity supply cannot sufficiently meet end-users' demands, decision makers will face a dilemma of either investing more funds in capacity expansions of the existing facilities or turning to other electricity production options or investing extra funds into electricity imports at raised prices. At the same time, SO_2 and NO_X are considered as the typical air pollutants to reflect environmental impacts during electricity generation.

Availabilities of renewable energy resources including hydro and wind powers are directly affected by their natural fluctuations, which can be presented as probability distributions. Thus their availabilities can be expressed as PDFs with fuzzy boundary intervals. Availabilities of coal and natural gas are presented as fuzzy boundary intervals due to the subjective estimation by decision makers. Technological conversion efficiencies vary with the facilities and quality of energy resources, and can also be presented as fuzzy boundary intervals. The rest of the parameters related to energy activities and environmental issues are expressed as intervals without distribution information. Electricity demands of the end users and the availabilities of energy resources are presented in Table 1. Relevant technical data and pollution emission factors are displayed in Table 2. A decision maker in this system is responsible for (1) allocating the limited energy resources effectively, (2) assigning scientific electricity generation schemes, and (3) identifying optimized capacity expansion plans for each conversion facility under minimized economic costs with consideration of the environmental impacts.

3.2. Result Analysis and Discussions

The $pi \in [0,1]$ levels represent probabilities at which the constraints are allowed to fail (Huang, 1998). A series of solutions can be obtained by fixing different levels. In this study, solutions under the three probabilistic levels of $p_i = 0.01$, 0.05, and 0.1 are examined with consideration of the realistic meanings. The detailed solutions under the three pi levels are presented in Figures 3 to 6 and Tables 4 to 5. The results indicate that along with the increase of electricity demands, less coal-fired, more hydro and wind powers based electricity would be generated. This is because of the strict environmental requirements and limited availabilities of fossil fuels.

Coal and natural gas supplies over the three periods under the three probabilistic levels (i.e., $p_i = 0.01$, 0.05, and 0.1, respectively) are presented in Figures 3 and 4. Coal would be the primary fossil fuel in the region compared to natural gas due to the relatively low price and operation cost. As the increase

Table 2. Technical Data for Each Conversion Technology

Conversion facility	Period		
	t = 1	t = 2	t = 3
Units of electricity production per unit of facility capacity (10^3 GWh/GW):			
Coal-fired power	[23.65, 26.72]	[25.84, 28.91]	[27.16, 30.22]
Gas-fired power	[22.02, 24.09]	[24.47, 24.97]	[26.28, 27.28]
Hydro power	[24.35, 24.35]	[25.09, 25.09]	[24.31, 27.28]
Wind power	[16, 16]	[15.14, 16.21]	[16.45, 18.52]
Units of energy carrier per unit of electricity production (TJ/GWh):			
Coal-fired power	[(11.52, 0.2), (12.42, 0.2)]*	[(10.98, 0.2), (11.88, 0.2)]	[(9.5, 0.2), (11.34, 0.2)]
Gas-fired power	[(8.64, 0.2), (9.54, 0.2)]	[(7.74, 0.2), (9.0, 0.2)]	[(7.2, 0.2), (8.1, 0.2)]
Hydro power	[(4.4, 0.2), (5.04, 0.2)]	[(4.22, 0.2), (4.86, 0.2)]	[(3.86, 0.2), (4.5, 0.2)]
Wind power	[(10.3, 0.5), (11.99, 0.5)]	[(9, 0.5), (10.5, 0.5)]	[(8.0, 0.5), (9.5, 0.5)]

* Represents a fuzzy boundary interval. The lower bound of the interval is a triangle number with the most possibilistic value of 11.52, and the variation to the left and right being 0.2; the upper bound of the interval is a triangle number with the most possibilistic value of 12.42, and the variation to the left and right being 0.2.

of electricity demand, the supplies of coal would rise to its maximum availability. Then the supplies of natural gas would correspondingly increase. There would be a sharp increase in natural gas supplies in period 3 due to the limited availability of coal and increased electricity demand. For instance, coal suplies would be [51.02, 199.01], [300.55, 380], and 360 × 10^3 TJ over periods 1 to 3, respectively; natural gas supplies would 0, [0, 59.92] and [277.33, 290] ×10^3 TJ over periods 1 to 3 under *pi* = 0.01, respectively.

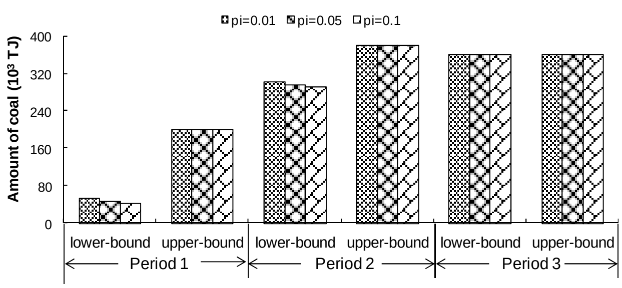

Figure 3. Coal supplies under three p_i levels.

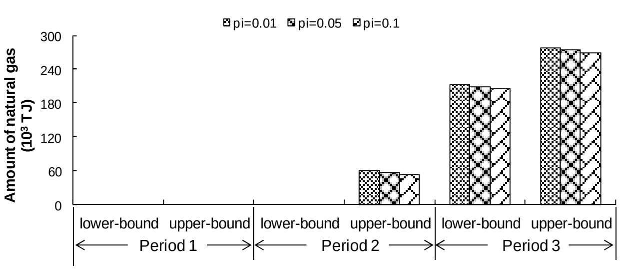

Figure 4. Natural gas supplies under three p_i levels.

Optimal electricity generation plans for each conversion technology over the planning horizon are presented in Table 4. Productions associated with all of these technologies would go up as the increase of electricity demands, especially hydro-power based electricity. Electricity generation from coal would rise with the increase of electricity demands to its maximize availability due to the limited coal supply, and then the electricity generation from natural gas would accordingly increase. Hydro as a renewable energy would take an indispensable place for electricity generation in this region. This is because of its relatively low operating costs and zero emissions of air pollution. For example, under p_i = 0.01, electricity generated from hydro would be [60.02, 65.12] × 10^3 GWh in period 3, while the amounts corresponding to coal-fired, gas-fired and wind powers would be [31.75, 37.89], [25.24, 37.38], and [12, 13.53] × 10^3 GWh respectively. Wind power would be mainly utilized in period 1 and would slightly increase with the rise of electricity demands over the three periods, being [10.37, 11.2], [10.5, 12.45], [12, 13.53] × 10^3 GWh under p_i = 0.01, respectively. The imported electricity as a potential recourse action takes an important role to maintain the security of the system. Due to its limited environmental impacts on local environment, the imported electricity would be up to its maximum value of 15 × 10^3 GWh over the planning horizon with no regards of electricity demands and p_i levels.

Table 3. Pollutant Emission Factors for Each Power Conversion Technology

Facility	Period		
	t = 1	t = 2	t = 3
SO_2 emission per unit of electricity production (tonnes/GWh):			
Coal-fired	[4.79, 5.17]	[4.42, 4.82]	[3.92, 5.12]
Gas-fired	[0.0342,0.0383]	[0.0317, 0.0357]	[0.0262, 0.037]
NO_X emission per unit of electricity production (tonnes/GWh):			
Coal-fired	[2.89, 3.19]	[2.68, 2.98]	[2.37, 2.67]
Gas-fired	[0.539, 0.579]	[0.50, 0.54]	[0.443, 0.483]

Due to the low residual capacity for each conversion facility, expansions would take place as shown in Table 5. It is indicated that the expansions would mainly occur in period 1. Taking p_i = 0.01 for example, the expansions for coal, natural gas, hydro and wind based facilities would be [0.05, 0.395], 0.8, 1.2, [0.648, 0.7] GW in period 1, respectively. Comparatively, in period 2, there would be no expansion for coal-fired conversion facilities. Expansions for natural gas, hydro and wind based facilities would be [0.105, 0.383], 0.7 and [0, 0.122] GW respectively. There would be a slight expansion of [0, 0.479] GW for hydro power based facilities in period 3. Also,

Table 4. Electricity Generation Plans for Each Power Conversion Technology under Different pi Levels (103 GWh)

facility	p_i	Period		
		t = 1	t = 2	t = 3
Coal-fired	0.01	[4.11, 17.28]	[25.3, 34.61]	[31.75, 37.89]
	0.05	[3.68, 17.28]	[24.86, 34.61]	[31.75, 37.89]
	0.1	[3.28, 17.28]	[24.42, 34.61]	[31.75, 37.89]
Gas-fired	0.01	0	[0, 7.74]	[34.24, 40.28]
	0.05	0	[0, 0.72]	[33.74, 40.28]
	0.1	0	[0, 6.66]	[33.24, 40.28]
Hydro	0.01	36.53	55.2	[60.02, 65.12]
	0.05	36.53	55.2	[60.02, 65.71]
	0.1	36.53	55.2	[60.02, 66.3]
Wind	0.01	[10.34, 11.2]	[10.5, 12.45]	[12, 13.53]
	0.05	[10.79, 11.2]	[10.94, 12.99]	[12.5, 14.12]
	0.1	11.2	[11.38, 13.53]	[13, 14.71]

Table 5. Capacity Expansion Plans for Each Power Conversion Technology under Different pi Levels (GW)

facility	p_i level	Period		
		t = 1	t = 2	t = 3
Coal-fired	0.01	[0.05, 0.395]	0	0
	0.05	[0.05, 0.395]	0	0
	0.1	[0.05, 0.395]	0	0
Gas-fired	0.01	0.8	[0.105, 0.383]	0
	0.05	0.8	[0.087, 0.383]	0
	0.1	0.8	[0.068, 0.383]	0
Hydro	0.01	1.2	0.7	[0, 0.479]
	0.05	1.2	0.7	[0, 0.503]
	0.1	1.2	0.7	[0, 0.527]
Wind	0.01	[0.648, 0.7]	[0, 0.122]	0
	0.05	[0.675, 0.7]	[0, 0.158]	0
	0.1	0.7	[0.002, 0.194]	0

it can be concluded that the expansions for natural gas-fired and hydro powers based facilities would be greater than that for coal-fired and wind powers based ones due to the increased environmental requirements. In period 1, expansions for natural gas-fired and hydro powers based facilities would be 0.8 and 1.2 GW under p_i = 0.01, respectively. At the same probability level, the values corresponding to coal-fired and wind powers facilities would be [0.05, 0.395] and [0.648, 0.7] GW, respectively under p_i = 0.01.

In order to satisfy the ambient environmental requirements, air pollution controlling measures would be adopted. Optimal plans for SO_2 and NO_X mitigation are presented in Figures 5 and 6. Since SO_2 and NO_X are mainly from coal- and gas-fired facilities, the trend of the mitigation targets for each pollutant would be consistent with the one of electricity generation targets for technologies based on fossil fuels. The amounts of treated SO_2 and NO_X would both increase when the amounts of electricity generated from fossil fuels increase. For example, under p_i = 0.01, when electricity generated by fossil fuels increases from [25.3, 42.35] × 10^3 GWh in period 2 to [65.99, 78.17] × 10^3 GWh in period 3, the amount of treated SO_2, NO_X would increase from [111.82, 167.09], [67.8, 107.31] × 10^3 tonnes in period 2 to [125.13, 195.45], [86.86, 119.8] ×10^3 tonnes in period 3, respectively.

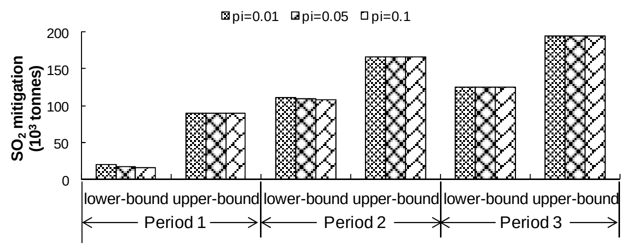

Figure 5. SO_2 mitigation plans under different p_i levels.

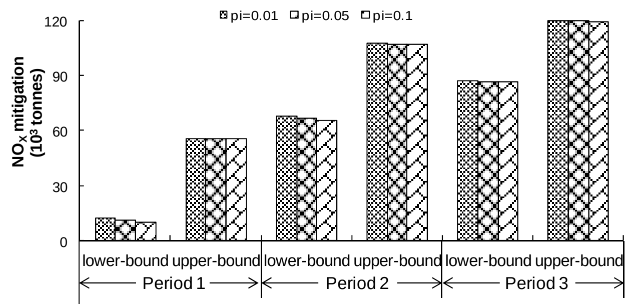

Figure 6. NO_X mitigation plans under different p_i levels.

Solutions of the developed model also indicate that any changes in *pi* levels would lead to different schemes regarding fossil fuel supply, electricity generation, capacity expansion and emission mitigation, since different *pi* levels correspond to different availabilities of renewable energy resources. As the increase of *pi* levels, the fossil fuel supplies would decrease, as well as the amounts of electricity generated from fossil fuels and the capacities of fossil fuel conversion technologies, For instance, in period 2 under p_i = 0.05, the electricity generated from coal-power and natural gas-power would be [24.86, 34.61], [0, 7.2] × 10^3 GWh, respectively. Capacity expansions for coal-fired, gas-fired would be 0, [0.087, 0.383] GW respectively. At the same time, the values would be [24.42, 34.61], [0, 6.66] × 10^3 GWh and 0, [0.068, 0.383] GW under p_i = 0.1, respectively. Comparatively, the electricity generated from renewable energies and the capacity expansions for renewable power conversion technologies would increase with the increase of *pi* levels. For example, in period 2 under p_i = 0.05, the electricity generated from hydro power and wind power would be 55.2, [10.94, 12.99] × 10^3 GWh, respectively; Capacity expansions for hydro power and wind power facilities would be 0.7, [0, 0.158] GW respectively. At the same time under p_i = 0.1, the values would be 55.2, [11.38, 13.53] × 10^3 GWh and 0.7, [0.002, 0.194] GW, respectively. Accordingly, the amounts of treated SO_2 and NO_X would decrease as the increase of p_i levels because the amounts of electricity generated from fossil fuels would be reduced. When p_i = 0.05, the amounts of treated SO_2 would be [17.61, 89.31], [109.89, 167.07], and [125.33, 195.43] × 10^3 tonnes over periods 1 to 3, respectively. The amounts of treated NO_X would be [10.62, 55.11], [66.63, 107.02], and [86.64, 119.52] × 10^3 tonnes over periods 1 to 3, respectively. While under $p_i = 0.1$, the values corresponding to treated SO_2 would be [15.69, 89.31], [107.95, 167.05], and [125.32, 195.4] × 10^3 tonnes, respectively. The values corresponding to treated NO_X would be [9.46, 55.11], [65.45, 106.73], and [86.42, 119.24] × 10^3 tonnes, respectively.

Different p_i levels would correspond to different optimal schemes related to electricity generation and capacity expansion options. The system costs would differ from each other under different p_i levels. Generally, when p_i level ascends, both the lower and upper bounds of system costs would decrease, and vice versa. When $p_i = 0.01$, the system costs would be \$[12,097.79, 16,938.46] × 10^6. Comparatively, the values would be \$[12,091.37, 16932.83], and \$[12,080.8, 16,927.2] × 10^6 under $p_i = 0.05$ and 0.1, respectively. A higher p_i level would correspond to a more favourable availability of renewable energy resources and a lower system cost due to the relaxed constraints (Tan et al. 2010). However, the risk of system failure would increase with the raised p_i levels, and the reliability of system would descend. In comparison, a lower p_i level would lead to higher strictness for the constraints of renewable energy availabilities, and would result in a higher system cost but a lower risk of system failure. Therefore, the p_i levels represent the probabilities at which the system would fail, and the tradeoffs between system costs and reliability would be reflected via the relationship between p_i and system costs.

The proposed LA-IFCCP is based on an integration of the existing inexact chance-constraint programming (ICCP), and lower-side attainment degrees based fuzzy linear programming techniques. It is capable of reflecting multiple formats of uncertainties during regional electric power generation systems planning, which can be expressed as discrete intervals, fuzzy sets, probabilistic distributions, and their combinations. And it allows those uncertainties to be incorporated within a general regional electric power system optimization framework. Moreover, it has advantages in computation efficiency compared with conventional fuzzy programming methods. The interrelationships between fuzzy coefficients can be reflected via lower side attainment degrees instead of using intervals at multiple α-cut levels, leading to lower computational requirements and higher practical applicability (Cai et al., 2009d). Furthermore, it is effective in reflecting tradeoffs between system reliability and energy resources availabilities. Probabilistic distributions of hydro and wind power availabilities can be integrated into the planning process and violation levels of hydro and wind power availability constraints can be quantified, which could help examine the relationship between system costs and reliability of satisfying constraints under multiple uncertainties. In general, LA-IFCCP improves upon the existing approaches for regional electric power generation systems planning, and enhances the robustness of optimization results.

4. Conclusions

In this research, a lower-side attainment degrees based inexact fuzzy chance-constraint programming (LA-IFCCP) was developed for supporting regional electric power generation systems planning under multiple uncertainties. Based on this method, uncertainties expressed as intervals, fuzzy sets, probabilistic distributions as well as their combinations could be effectively communicated into the optimization system, greatly avoiding over-simplification of real-world problems. The fuzzy coefficients in the model could be de-fuzzied into the corresponding ones without introducing any additional constraints, enhancing the computation efficiency. Moreover, LA-IFCCP had an advantage in system reliability reflection since it could quantify the constraint-violation levels, which was important for maintaining the security of electricity generation.

The developed method was then applied to support the planning of a representative electric power generation system to demonstrate its applicability. Interval solutions under different *pi* levels could be obtained through a two-step interactive algorithm, which could help decision makers foster a comprehensive overview of energy supply, electricity generation, capacity expansion and pollutant mitigation with a minimized net system cost. The relationships between system costs and reliability could be reflected through the analysis of the solutions under different p_i levels, which could quantify the violation of constraints about renewable energy resources availabilities.

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