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A Dual-Uncertainty Two-Stage Fractional Programming Model for Regional Power Systems in the Province of Ontario, Canada

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ABSTRACT. This study proposed a dual-uncertainty two-stage fractional power system management (DUTSF-PSM) model to deal with uncertainties and dual objectives in the power management system of Ontario. This model integrates interval linear programming (ILP), chance-constrained programming (CCP), mixed-integer linear programming (MILP), and two-stage stochastic programming (TSP) methods into the framework of a linear fractional programming (LFP) model. Two-objective issues and capacity expansion schemes under multiple uncertainties can be addressed by the DUTSF-PSM model. Economic and environmental elements are considered in the objective function of the DUTSF-PSM model at the same time in order to get maximal system benefit with minimum environmental influence. This model can tackle effectively the tradeoff between the economic and environmental objectives. Through the DUTSF-PSM model for power systems in Ontario, the maximal system efficiency based on the least environmental influence under different levels of constraint-violation probabilities can be achieved. The results indicate that both hydroelectric and wind power have development potential when the economic and environmental factors are considered in the objective function at the same time. In addition, the results of factorial analyses reflected that the effect of CO_2 emission of each power generation technology on the system revenue is most significant among the chosen three factors.

Keywords: reginal power system, interval linear programming, two-stage stochastic programming, factorial analysis

1. Introduction

An effective and appropriate programming for a regional power system is essential and vital to the development of the economy and the protection of the environment all around the world (Hu et al., 2011; Chen et al., 2015; Cai et al., 2019; Huang et al., 2019; Xie et al., 2019). However, many challenges exist during the construction of the power system management model due to some problems of the power supply, demand and allocation among different generation technologies. Because there are a variety of factors affecting the structure of the power system and allocation plans among different power generation technologies, it is complicated to build an effective management model for the power system. Besides the complexity from various factors, many uncertainties in the power system increase the difficulty for the construction of an appropriate management model for the power system (Yan and Luh, 1997; Martins and Borges, 2011; Zhao et al., 2013; Lindenschmidt and Rokaya, 2019). These uncertainties include some random parameters in the power system which are related to the power demand, power energy availability, and the capacity of power generation facilities (Ambec and Crampes, 2012; these parameters may be represented as interval values instead of random values or fuzzy sets when distribution and membership functions are unknown (Tong, 1994). Moreover, multiple objectives should be usually applied to a management model in order to consider several aspects of a power system at the same time (Heinrich et al., 2007; Zhan et al., 2014). For example, sometimes the economic benefit is expected to be maximized when the CO_2 emission of the system is as low as possible. Therefore, an effective reginal power management model should take economic and environmental issues into account under multiple uncertainties.

Many approaches have developed to deal with the uncertainties and complexities of a linear programming problem. For dealing with uncertainties in linear programming problems, a large number of previous studies have proposed and developed many methods including interval linear programming (ILP), fuzzy linear programming (FLP), chance-constrained programming (CCP), and two-stage stochastic programming (TSP) (Huang et al., 1992; Liu, et al., 2009; Xu et al., 2009, 2010; Li et al., 2019). When some integer factors exist in the programming system, mixed-integer linear programming (MILP) can be used to solve this kind of problems (Liu et al., 2011; Cheng et al., 2017; Badiozamani et al., 2019). These approaches have

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been applied in the programming problem of power system. For example, Li et al. (2010) integrated ILP and MILP into multi-stage linear programming to tackle the reginal electric power system planning problem. Wang et al. (2011) used CCP and TSP to deal with the uncertainties of the wind power output in a power system. Tomsovic (1992) solved the voltage control problem of a power system with FLP approach.

In terms of multi-objective programming issues of a power system, a large number of efforts have done in previous studies. Abido (2006) proposed several algorithms for solving multiple objective electric dispatch problem. Linear fractional programming (LFP) have been proposed to deal with two objectives in a programming problem (Cui et al., 2015; Song et al., 2018). Based on the LFP method, various advanced technologies, and methods are integrated to address complex uncertainties in the programming model. TSP, CCP, and MILP methods have been applied into the framework of FLP model to form a chance-constrained two-stage fractional programming (CTFP) approach to solve multiple uncertainties in a dual-objective programming problem. However, the distribution function of some parameters in the CTFP model are not known. Therefore, this study tried to integrate ILP method into a CTFP model to formulate a dual-uncertainty two-stage fractional programming (DUTSF) model to address uncertainty expressed as interval in a dual-objective programming problem. Furthermore, this study developed a dual-uncertainty two-stage fractional power system management (DUTSF-PSM) model for the decision maker in Ontario to manage the reginal power system more appropriately.

2. Overview of the Ontario Power System

2.1. Overview of the Province of Ontario

Ontario is the leading manufacturing province in east-central Canada with a total area of 1,076,395 km^2 (Wolfe and Gertler, 2001; Diamond et al., 2009; Fleet et al., 2015). It is bordered by the province of Quebec to the east and northeast, James Bay and Hudson Bay to the north, Manitoba to the west, and to the south by several U.S. states including (from east to west) New York, Pennsylvania, Ohio, Michigan, and Minnesota. Regarding the land area, Ontario is the second-largest province of Canada (Michaud et al., 2012; Wang et al., 2014). In terms of population, it is the most populous province of Canada (Crowcroft et al., 2019; Jin et al., 2019). The populartion of Ontario reached 14.49 million which is 40% of the Canadian population on April 1, 2019, with an increase of 5% people comparing with the population in 2015. Concerning the economic development, Ontario's nominal gross domestic product (GDP) accounted for 38.7% of Canadian national GDP with $854,272 million in 2018. Compared to the year of 2015, the GDP of the province of Ontario in 2018 increased 26.33%.

2.2. Power System of Ontario

Most of the resources of the power system in Ontario are renewable or environmentally friendly including hydroelectric, wind, solar, biomass, and nuclear power (Winfield et al., 2010; Hoicka and Rowlands, 2011; Stokes, 2013). According to the government statistics report of Ontario, the nuclear power generation is currently one of the main power technologies for the power system in Ontario (Mukherjee et al., 2019). The province of Ontario has an abundance of uranium resources. The nuclear power accounted for more than 30% of Ontario's electricity (Rosenbloom, 2019). Three nuclear plants are in Ontario have the power generation capacity of 13,009 megawatt (MW) in 2019. Some of the reactors in these plants are planned closed after 2020. For example, the reactors including Pickering A1 and Pickering A4 are planned to be close in 2022. Pickering B5, B6, B7, and B8 are planned to be close in 2024. Darlington 1, 2, 3, and 4 are planned to be close in 2025. All the motioned reactors planned to close are currently operated by the Ontario Power Generation.

Besides nuclear power, another main power resource for the power system in Ontario is hydroelectric. As a kind of clean natural energy, hydraulic resources are used to generate power without greenhouse gas emission which can help the government to achieve carbon reduction targets (Kaya et al., 2019). The geomorphological feature of Ontario provides the possibility for development of hydroelectric. There are more than 130 hydroelectric generation stations with the total power generation capacity of 8,130.81 gigawatt (GW) in Ontario. Among them, the biggest hydroelectric generating station is the Sir Adam Beck Generating Station II with the power generation capacity of 1,499 MW.

Solar energy is another kind of renewable energy which is widely existed in the nature. As a clean energy, solar can be converted to electricity through solar panels. According to the statistical data from National Resources Canada, the electricity of 1,167 kilowatthour (kWh) can be produced by 1 kilowatt (kW) solar system per year on average in Ontario. In the scheduled additions for electricity system, 20% of projects are related to solar power energy system. Although Ontario has the lowest solar installation costs in Canada and many solar installation companies (Sow et al., 2019), it lacks an incentive policy for solar power system and electricity rates in Ontario. As a result, the solar power system development in Ontario is not as fast as that in other provinces in Canada.

In terms of the wind power generation technology, Ontario is the largest wind market in Canada. Until December 2018, Ontario remained the leader province in Canada in clean wind energy with the installed power generating capacity of 5,076 MW (Conlon et al., 2019). According to the Statistics Canada in 2017, the wind energy satisfied the 8% of electricity demand in Ontario. Because of the low cost and no carbon emission of wind energy the government in Ontario develops some policies to encourage the development of wind power. The average cost of wind power capacity is as low as 3.7 cents per kWh which makes the wind power technology to be the lowest cost option for the power system in Ontario.

Biomass which is the second largest renewable energy resource following hydroelectricity is used as a kind of power generation resources for the power system in Ontario. As a kind of non-fossil organic materials, biomass stores amount energy and has the potential to replace the position of fossil fuel like coal in the energy system and power system. In April 2014, the event that all the stored coal in Ontario was burned out made Ontario be the first administrative district in North America to fully give up coal as a source of power generation and choose biomass as the alternative fuel to produce electricity for the power system in Ontario.

Among all kinds of traditional energy resources (coal, oil, natural gas, diesel and so on) natural gas has the competitive advantages on several aspects such as the price, the safety, and the cleanliness. Compared with other fossil fuel, natural gas is more environmentally friendly because it is cleaner when it is burned. Besides, natural gas is easier for storage and transmission. In the power system in Ontario, it still takes an important position due to its low cost and complete infrastructure.

2.3. Problem Statement

As the describe above, the power system in Ontario is supported by several kinds of energy resources including hydroelectric, wind, solar, biomass, nuclear, and natural gas. Among them the hydroelectric, wind, solar are renewable and clean energies because no CO_2 emission when they are used to generate electricity. The biomass is also renewable energy although it emits CO_2 when it is used to convert to power. Natural gas is the only one traditional fossil fuel which is still used to support the power system in Ontario. Facing the further carbon emission reduction targets, decision makers must trade off the environmental factors and the economic elements when they decide the power generation task allocated for each power generation technology. In addition, multiple uncertainties are existed in the power system of Ontario. For example, the wind power depends on the speed of the wind. Solar power is affected by the solar irradiation. In other words, these two kinds of renewable energies rely on the weather conditions. However, the weather is variable all the year round. Normally, according to the statistics documents for the wind speed and the solar irradiation the distribution of these two kinds of energies can be achieved. It is necessary to consider this kind of uncertainty when the decision makers make the power allocation programming. Beside the uncertainty which comes from the resource feature, another uncertainty may come from the power market regulation. That means all the parameters in the power system are always known in a certain rang instead of a precise value. This kind of uncertainties also should be considered when a decision is made to allocate the power generation tasks. Moreover, the generation always rely on the power demand. However, the power demand levels are not constant all the time. Sometimes the power demand is following a specific distribution at different level. This random event which happens after the power generation targets are decided can result in additional power generation activity which can bring more benefits for the power system. Therefore, an appropriate model for planning the long-term power allocation programming of the power system in Ontario.

The problem considered to be solved in this study is how to make an appropriate power generation allocation scheme and the capacity expansion plan for each type of power generation technology. The complexities of this problem related to the power system in Ontario include: (1) how to effectively plan the power generation allocation for each technology; (2) how to deal with the uncertainties which exist in this system; (3) how to make a reasonable plan for the capacity expansion of all the facilities in this system under multiple uncertainties; (4) how to maximize the benefit from this power system based on the low CO_2 emission which are considered in the objective function of this system; (5) how to indicate the excess economic benefit due to the additional power generation on the basis of the previous decision; (6) how to trade off the relationship between the benefits and the reliability of this power system.

3. Development of DUTSF-PSM Model

3.1. Dual-Uncertainty Two-Stage Fractional Programming (DUTSF) Model

LFP model is often used to deal with multi-objective optimizing programming problem. The general form of LFP model can be described as follows:

$$Max\ f(X) = \frac{CX + \alpha}{DX + \beta} \tag{1a}$$

subject to:

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

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

where $C \in \{R\}^{1 \times n}$, $D \in \{R\}^{1 \times n}$, $A \in \{R\}^{m \times n}$, $B \in \{R\}^{m \times 1}$, $X \in \{R\}^{n \times 1}$; α and β are constant parameters; $\{R\}$ is a set of real numbers. In this general form, all the parameters are determined real numbers. However, there exist various uncertainties in real world. Meanwhile, different kinds of characteristics will be attached to parameters and variables in the model. Some values should be integer in real cases and some of them are stochastic values which follow specific distribution function. As a result, it is necessary to apply different types of uncertainty expression and constraints to values in the general LFP model. Zhu et al. (2014) integrated the interval relationships and integer characteristics into the general LFP model and formed an inexact mixed-integer fractional programming (IMIFP) model. Zhou et al. (2015) introduced CCP and TSP into the general LFP model and formed chance-constrained two-stage fractional reginal energy model (CTFO-REM). In order to reflect dual uncertainties in real word, this study used interval and chance constrained methods to develop the general LFP model. Meanwhile, two-stage stochastic programming was also integrated into the general LFP model to help the decision maker to predict effects of stochastic events on established decision. As a result, a DUTSF has been developed in this study. Based on model 1, both parameters and variables were expressed as interval values. TSP method was used to deal with stochastic event. For constraints, CCP approach was introduced into this model to handle stochastic parameters. Assumed that the B in the right hand of the constraints in model 1 is follow a specific stochastic distribution and the new DUTSF model used $B(k)$ represent the sets with random elements defined on a probability space K where k

$\in K$ is satisfied. The DUTSF model can be expressed as follows:

$$Max\ f^{\pm}(X^{\pm}) = \frac{C_1^{\pm} X^{\pm} + E(D_1^{\pm} Y^{\pm}) + \alpha^{\pm}}{C_2^{\pm} X^{\pm} + E(D_2^{\pm} Y^{\pm}) + \beta^{\pm}} \tag{2a}$$

subject to:

$$A_s^{\pm} X^{\pm} + A'^{\pm}_s Y^{\pm} \le b(k)^{q_s}, \qquad s = 1,2,...,S;\ h = 1,2,...,v \tag{2b}$$

$$A_i^{\pm} X^{\pm} + A'^{\pm}_i Y^{\pm} \le W_i^{\pm}, \qquad i = 1,2,...,m; \tag{2c}$$

$$x_j^{\pm} \ge 0, \qquad j = 1,2,...,k_1 \tag{2d}$$

$$y_j^{\pm} \ge 0, \qquad j = 1,2,...,k_2 \tag{2e}$$

$$x_j^{\pm} \ge 0, \qquad j = k_1 + 1,...,n_1 \tag{2f}$$

$$y_j^{\pm} \ge 0, \qquad j = k_2 + 1,...,n_2 \tag{2g}$$

where $x_j^{\pm} \in \{X^{\pm}\}^{n \times 1}$, $y_j^{\pm} \in \{Y^{\pm}\}^{n \times 1}$, $b(\mathrm{k}) \in B(\mathrm{k})$; $X^{\pm}$ and $Y^{\pm}$ are first- and second-stage decision variables, respectively; $C_1^{\pm}$, $C_2^{\pm}$, $D_1^{\pm}$, and $D_2^{\pm}$ are interval coefficients in fractional objective function; $A_s^{\pm}$ and $A'^{\pm}_s$ are interval coefficients in the constraint s; $A_i^{\pm}$ and $A'^{\pm}_i$ are interval coefficients in the constraint i; $b(k) \in B(k)$, and $B(k)$ denotes sets of random parameters defined on a possibility space K; and $W_i^{\pm}$ is a random parameter in right-hand of the constraint i. According to previous studies about CTFO-REM model, the DUTSF model can be solved by using branch-and-bound method and linear programming approach. The converted form can be solved by Lingo 11.0 as addressed in previous studies (Zhu et al., 2014).

The developed DUTSF model can solve the problems with uncertainties expressed as interval values and stochastic parameters. Moreover, this model can also help a policy maker to make a better decision based on further prediction of the level of the scarcity or surplus of decision valuables which may be due to some stochastic events. In the first stage, a decision should be made before a stochastic matter happen. Then the second stage is used to predict the deficiency or surplus of decision variables. For the objective function in DUTSF, both of numerator and denominator could be economic indicators or yield indexes. Sometimes, the numerator and denominator could be indices which described different aspects of a system. For example, the numerator could be economic index when the denominator represents the product yield of the system.

All in all, for the proposed DUTSF model, there are several primary advantages which can be summarized as follows: (1) it can deal with the tradeoffs among multiple objectives and provide an optimized solution for the studied system; (2) it can address effectively the uncertain parameters whose probability distribution and membership function are unknown in the systems; (3) it can reveal the relationship between the decision made in first stage and the implied economic punishment in the second stage when the stochastic event happened after the predefined policies; (4) it can help the decision maker to analyze the rationality of capacity expansion planning; (5) it can be used to get the desired solution at different level of constraint violation.

3.2. Development of DUTSF-PSM Model

Based on the proposed DUTSF model, a dual-uncertainty two-stage fractional power system management (DUTSF-PSM) model is developed for the policy makers of Ontario's power system to get more reliable decision choices supporting the power system management in the province of Ontario. According to the basic condition of the power system in Ontario, this study considers the economic benefits and environmental effects in the objective function of DUTSF-PSM model at the same time. Here the net benefit was considered as the result of total revenue from electricity sales minus total cost for electricity generation. In this model, the power generation of different power generation types in different planning period is set as decision variables. Since the power generation sometimes varies based on the power generation demand whose values are various at different levels, additional revenue will be generated due to the power generation beyond the planned portion. In order to reflect this part of revenue from excess power generation, the second stage variables for generation and primary energy are also set as decision values in this model. In addition, the variables about the capacity expansion of different power generation technologies are also included in this model. Meanwhile, the environmental factors are also included in the object of this model. This study mainly considered the CO_2 emission in the environmental target of this model. As a result, in the DUTSF-PSM model, the object is to maximize the net benefit of the power system on the base of less CO_2 emission. In detail, the objective function of this model is shown as follows:

$$\begin{aligned} Max\ f^{\pm} &= \frac{Revenue\ from\ power\ generation\ sales}{the\ amount\ of\ CO_2\ emission} \\ &- \frac{Cost\ of\ power\ generation}{the\ amount\ of\ CO_2\ emission} \\ &= \frac{f_1^{\pm} - f_2^{\pm} - f_3^{\pm}}{f_4^{\pm}} \end{aligned} \tag{3a}$$

The objective function is the sum of elements $f_1^{\pm}$, $f_2^{\pm}$, $f_3^{\pm}$, and $f_4^{\pm}$. These elements are shown as follows:

(1) Total revenue from power generation sales:

$$f_1^{\pm} = \sum_{i=1}^{6}\sum_{t=1}^{4} PRE_t^{\pm} \cdot XE_{it}^{\pm} + \sum_{i=1}^{6}\sum_{t=1}^{4}\sum_{h=1}^{3} p_h^{\pm} \cdot PRE_t^{\pm} \cdot YE_{ith}^{\pm} \tag{3b}$$

(2) Total cost of primary energy supply for power generation plants:

$$f_2^{\pm} = \sum_{j=1}^{3}\sum_{t=1}^{4} CEP_{jt}^{\pm} \cdot XP_{jt}^{\pm} + \sum_{j=1}^{3}\sum_{t=1}^{4}\sum_{h=1}^{3} p_h^{\pm} \cdot CEP_{jt}^{\pm} \cdot YP_{jth}^{\pm} \tag{3c}$$

(3) Total cost during power generation process (operation cost, maintenance cost, and capacity expansion cost):

$$f_3^{\pm} = \sum_{i=1}^{6}\sum_{t=1}^{4} COE_{It}^{\pm} \cdot XE_{It}^{\pm} + \sum_{i=1}^{6}\sum_{t=1}^{4}\sum_{h=1}^{3} p_h^{\pm} \cdot COE_{It}^{\pm} \cdot YE_{ith}^{\pm} + \sum_{i=1}^{6}\sum_{m=1}^{3}\sum_{h=1}^{4} CEE_{imt}^{\pm} \cdot CE_{imt}^{\pm} \cdot ZE_{imt}^{\pm} \quad (3d)$$

(4) Total CO_2 emission of power generation system:

$$f_4^{\pm} = \sum_{i=1}^{6}\sum_{t=1}^{4} ECO_{it}^{\pm} \cdot XE_{it}^{\pm} + \sum_{i=1}^{6}\sum_{t=1}^{4}\sum_{h=1}^{3} p_h^{\pm} \cdot ECO_{it}^{\pm} \cdot YE_{ith}^{\pm} \quad (3e)$$

The constraints of DUTSF-PSM model including the following aspects:

(1) Constraints of mass balance constraints between energy resources and power generation:

$$(XE_{4t}^{\pm} + YE_{4th}^{\pm}) \le GE_{41t}^{\pm}(XP_{1t}^{\pm} + YP_{1th}^{\pm}) \qquad \forall t,h \quad (3f)$$

$$(XE_{5t}^{\pm} + YE_{5th}^{\pm}) \le GE_{52t}^{\pm}(XP_{2t}^{\pm} + YP_{2th}^{\pm}) \qquad \forall t,h \quad (3g)$$

$$(XE_{6t}^{\pm} + YE_{6th}^{\pm}) \le GE_{63t}^{\pm}(XP_{3t}^{\pm} + YP_{3th}^{\pm}) \qquad \forall t,h \quad (3h)$$

(2) Constraints of total electricity demand:

$$\sum_{i=1}^{7}(XE_{it}^{\pm} + YE_{ith}^{\pm}) \ge DM_{th}^{\pm} \qquad \forall t,h \quad (3i)$$

(3) Constraints of power generation capacity:

$$XE_{it}^{\pm} + YE_{ith}^{\pm} \le \sum_{m=1}^{3}(RE_i^{\pm} + CE_{imt}^{\pm} \cdot ZE_{imt}^{\pm}) \cdot CEF_{ith}^{\pm} \qquad \forall i,t,h \quad (3j)$$

(4) Constraints of power generation technology:

$$XE_{it}^{\pm} + YE_{iht}^{\pm} \le RAE_i^{\pm} \cdot \sum_{m=1}^{3}(RE_i^{\pm} + CE_{imt}^{\pm} \cdot ZE_{imt}^{\pm}) \cdot CEF_{ith}^{\pm} \qquad \forall i,t,h \quad (3k)$$

(5) Constraints of CO_2 emission target:

$$(XE_{it}^{\pm} + YE_{ith}^{\pm}) \cdot ECO_{it}^{\pm} \le AET_{th}^{\pm} \qquad \forall i,t,h \quad (3l)$$

(6) Constraints of power generation capacity expansion options:

$$\sum_{m=1}^{3} ZE_{imt}^{\pm} \le 1 \qquad \forall i,t \quad (3m)$$

$$ZE_{imt}^{\pm} = 0 \text{ or } 1 \qquad \forall i,m,t \quad (3n)$$

(7) Constraints of power generation and primary energy resources:

$$\Pr\{XP_{jt}^{\pm} + YP_{jth}^{\pm} \le UP_{jt}^{\pm}(k)\} \ge 1 - q_{jth,UP} \qquad \forall j,t,h \quad (3o)$$

$$\Pr\{(XE_{it}^{\pm} + YE_{ith}^{\pm}) \ge L_{it}^{\pm}\} \ge 1 - q_{th,L} \qquad \forall i = 1,2,3,t,h \quad (3p)$$

$$\Pr\{(XE_{it}^{\pm} + YE_{ith}^{\pm}) \le U_{it}^{\pm}\} \ge 1 - q_{th,U} \qquad \forall i = 1,2,3,t,h \quad (3q)$$

(8) All decision variables are non-negative:

$$XE_{it}^{\pm}, XP_{jt}^{\pm}, YE_{ith}^{\pm}, YP_{jth}^{\pm}, ZE_{imt}^{\pm} \ge 0 \qquad \forall i,j,m,t,h \quad (3r)$$

The meanings of all the subscripts, decision variables, and parameters are described in the Appendix A. In order to solve the DUTSF-PSM model, firstly according to the algorithm for solving mixed integer linear fractional programming addressed by Zhu et al. (2014) the original model need to be converted to a form without fractional equation. Then the second step is to use the interval linear programming solution approach to solve the non-fractional programming achieved in the step one. The final step is to transfer the achieved solutions to corresponding original decision variables. This study attempted to use the proposed DUTSF-PSM model to analyze the power systems development for the twenty years from 2016 to 2035 which was divided into four periods in this model. Since many factors in this power system may affect the allocation of power generation tasks for each power generation technology, this study arranged several different scenarios to further discuss the influ-

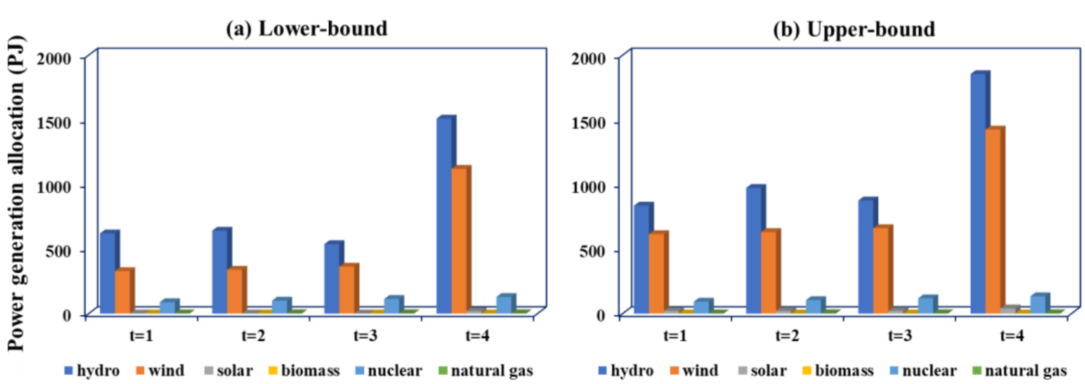

Figure 1. (a) Lower-bound and (b) upper-bound of power generation targets under q_s = 0.01 in scenario 1.

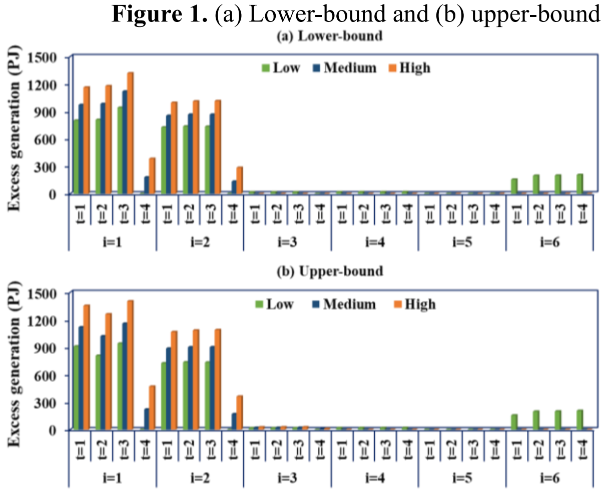

Figure 2. (a) Lower-bound and (b) upper-bound of excess power generation activities under different levels under q_s = 0.01 in scenario 1.

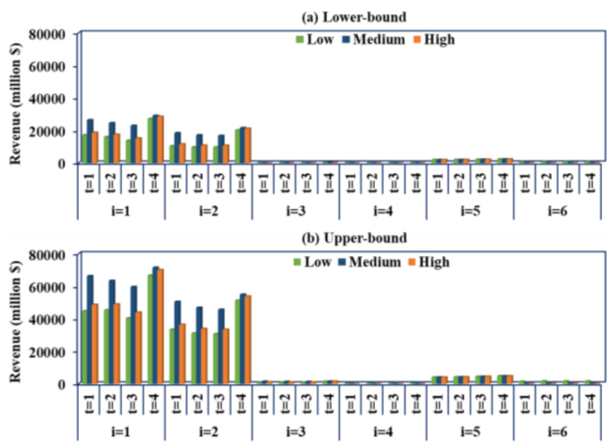

Figure 3. (a) Lower-bound and (b) upper-bound of revenue from different kinds of power generation technologies under different excess levels in q_s = 0.01 in scenario 1.

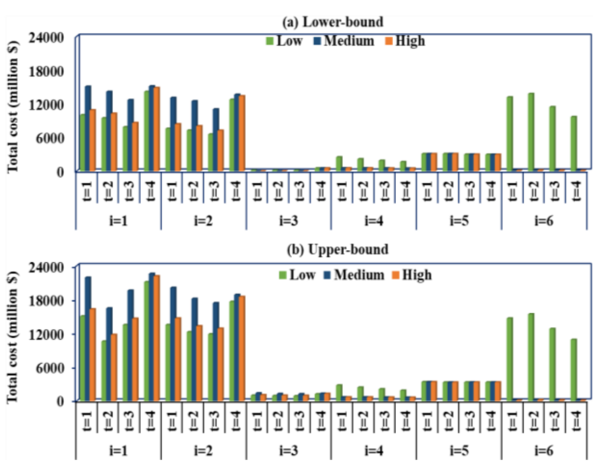

Figure 4. (a) Lower-bound and (b) upper-bound of total system cost from different kinds of power generation technologies under different excess levels under q_s = 0.01 in scenario 1.

ence of different factors on the power system in Ontario. In detail, several different scenarios, and the main factors to be discussed in these scenarios are described as follows: (1) In scenario 1, the DUTSF-PSM model was used to analyze the power system in Ontario. That means the economic and environmental factors are considered as goals which are included in the objective function of DUTSF-PSM model; (2) In scenario 2, the environmental goal is removed from the objective function. The results obtained under scenario 2 will be compared with that achieved under scenario 1; (3) In factorial analysis, the effects of several factors including prices of power generation sales (PRE_t in DUTSF-PSM model), the cost of primary energies (CEP_{jt}), cost during power generation process (COE_{it}), and CO_2 emission of each power generation technology (ECO_{it}) on revenue and cost of the power system will be discussed in detail.

4. Results Analysis and Discussion

Different power generation technologies have been included in the power system in Ontario. Some of these technologies are environmentally friendly and emission no CO_2, while others can result in environmental problems due to the emission of CO_2. The power generation allocation scheme and the capacity expansion plan for each type of power generation technology will be different under different scenarios. As a result, it is necessary to discuss the optimization of power system in Ontario under different scenarios. Besides, effects of different factors on the power system in Ontario will be investigated because such effects play important roles in the planning progress for the optimization of the Ontario's power system.

4.1. Optimization of Power System in Ontario under Scenario 1

The basic assumption in scenario 1 is the q_s motioned in model 2 is 0.01. Solutions of power generation targets, excess power generation, revenue and cost using DUTSF-PSM model under q_s = 0.01 are shown in Figures 1 ~ 4. In addition, results of capacity expansion options and CO_2 emissions are shown in Tables 1 ~ 2. In detail, Figure 1 provides the power generation targets of various technologies in different periods for the power system in Ontario under q_s = 0.01. Excess powers generated by six types of technologies for Ontario's power system under low, medium, and high levels are presented in Figure 2. The revenue and cost of the power system based on optimal solutions under q_s = 0.01 are shown in Figure 3 and Figure 4, respectively. Besides, capacity expansion plans and CO_2 emission amount during generation process of the power system under scenario 1 are listed in Table 1 and Table 2, respectively. For example, during 2016 ~ 2020 period (t = 1 in the DUTSF-PSM model) the power generation targets from the hydro, wind, solar, and nuclear power generation are in the ranges of [620.02, 835.21], [328.54, 614.60], [0.21, 19.93], and [88.02, 91.70] petajoule (PJ), respectively. In scenario 1, there is no power generation target activity from biomass power generation technology during period 1 (t = 1). 0.93 J of Natural gas-fired power generation are required during period 1 under scenario. When all the random values are at low level, the excess power generations of the six kinds of technologies (i = 1, 2, 3, 4, 5, 6 in the DUTSF-PSM model) are in the ranges of [801.31, 1162.89], [726.74, 995.21], [17.32, 17.32], [18.87, 18.87], [0, 0], [156.72, 156.72] PJ, respectively. In terms of primary energy, this study just considers biomass, uranium, and natural gas (j = 1, 2, 3 in the DUTSF-PSM model) as the primary energy resources of the bioenergy, nuclear, and natural gas-fired power generation technologies (i = 4, 5, 6 in the DUTSF-PSM model). According to the result of DUTSF-PSM model, the decision maker decides no biomass to be invested into the power systems during period 1 in Ontario. However, when the demand variables which follow a specific distribution are at low level, the excess need for bioenergy will be 75.50 PJ. Additionally, the binary variables of expansion options provide the optimal capacity expansion planning for the power system in Ontario during each period.

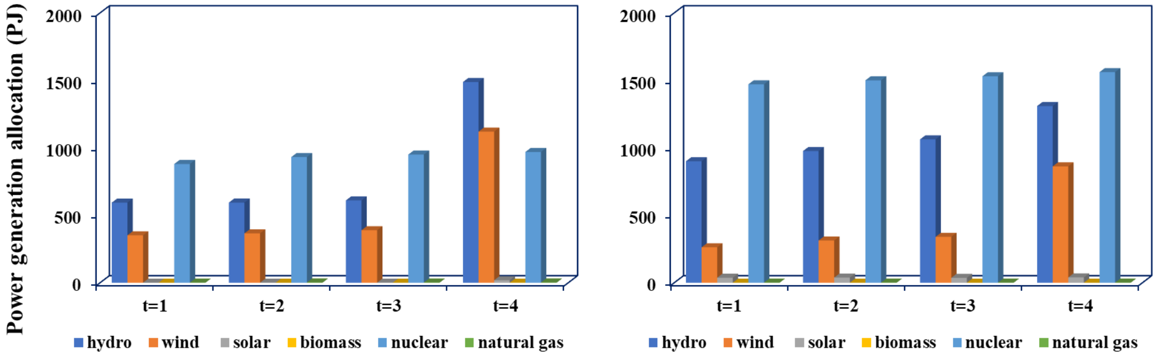

Figure 5. (a) Lower-bound and (b) upper-bound of power generation targets under q_s = 0.01 in scenario 2.

According to these calculation results and from Figure 1, it is obvious that the hydroelectricity and wind power generation technologies are two kinds of main resources for the power system in Ontario during the future 20 years. Although nuclear power is not as much as these two kinds of power generation, it provides more power than biomass and natural gas during 2016 ~ 2035 for power system in Ontario. The target power generations of different types of technologies decline over the whole planning horizon (Figure 1). Because the random characteristic of demand and the actual amount of power generation always depends on the actual electricity consumption and power demand, excess power generation will be existed when the random demand of power generation is at different levels as Figure 2 shows. Excess generations from hydroelectricity and wind power generation technologies increase with the raise of the actual power demand while the natural gas-fired power generation decreases when the demand level increases. For example, the lower bound of excess power generation from hydroelectricity is 801.31 PJ at low demand level and increases to 1,162 PJ at high level during period 1. The lower bound of excess wind power is 726.74 PJ at low demand level and increases to 995.21 PJ at high level during the first stage of planning horizon. However, the lower bound of excess power generation from natural gas-fired decreases from 156.72 to zero PJ when the demand level increases from low level to high level.

Although excess power generation of hydro and wind power generation technologies reach their maximal values at high demand level, the revenue and total cost do reach their maximal values at medium demand level rather than at high demand level as Figure 3 and Figure 4 indicate. For nuclear power generation technology, the revenue and total cost do not change at different demand levels over the entire planning horizon although the power generation target of nuclear power increase through the whole planning period. In addition, Figure 4 indicates the total cost of natural gas-fired power generation is higher than that of nuclear power while the revenue generated from natural gas-fired power generation is lower than that come from nuclear power generation which is shown in Figure 3. The revenue from the nuclear power mainly due to the generation target during the planning period. The high cost of natural gas-fired power generation under low demand level in each period is mainly because of the excess power generation of natural gas-fired power generation technology. Meanwhile the excess primary energy supply for natural gas-fired is as high as [414.87, 432.16], [479.53, 499.51], [439.89, 458.22], [407.84, 424.84] PJ under low demand level during periods 1, 2, 3, 4, respectively. These values are much higher than that of primary energy supply for natural gas-fired power generation technologies under medium and high demand levels. This may result in the increase of the cost of natural gas-fired power generation at low demand level.

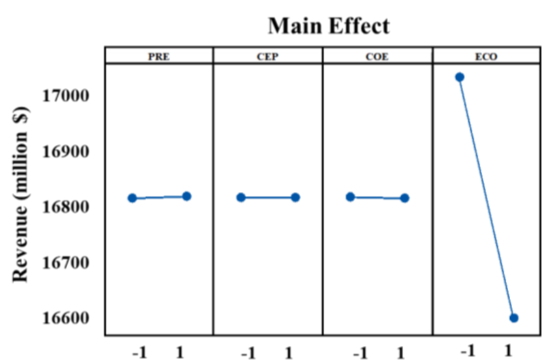

Figure 6. The main effect graph of the selected factors (–1 represents low level, 1 represents high level).

The capacity expansion plans during different periods for each power generation technology are shown in Table 1. Re-

Table 1. Solution of Capacity Expansion Options for Different Power Generation Technologies in Each Period Under $q_s = 0.01$ in Scenario 1

Power generation technology	Capacity expansion option	$t = 1$	$t = 2$	$t = 3$	$t = 4$
Hydroelectric ($i = 1$)	$m = 1$	0	0	0	0
	$m = 2$	0	0	0	0
	$m = 3$	1	1	1	1
Wind ($i = 2$)	$m = 1$	0	0	0	0
	$m = 2$	0	0	0	0
	$m = 3$	1	1	1	1
Solar ($i = 3$)	$m = 1$	0	0	0	0
	$m = 2$	0	0	0	0
	$m = 3$	0	0	0	0
Biomass ($i = 4$)	$m = 1$	0	0	0	0
	$m = 2$	0	0	0	0
	$m = 3$	1	1	1	1
Nuclear ($i = 5$)	$m = 1$	0	0	0	0
	$m = 2$	0	0	0	0
	$m = 3$	0	0	0	0
Natural gas ($i = 6$)	$m = 1$	0	0	0	0
	$m = 2$	0	0	0	0
	$m = 3$	0	0	0	0

develop the hydroelectricity, wind power generation and bioenergy power generation for the goal in which the net benefit of the power system is maximized while the CO_2 emission is minimized at the same time. In terms of the CO_2 emission from the power system, the results based on the optimal power generation targets, excess power generation under different demand level and capacity expansion solutions are shown in Table 2. According to this table, hydro, wind, and solar power generation technologies are clean power energy without CO_2 emission. Under low demand level, the CO_2 emission of bioenergy power generation is higher than that under other levels of power demand.

4.2. Optimization of Power System in Ontario under Scenario 2

According to results received in scenario 1, when the environmental factor is considered in the objective function the hydroelectric and wind power are two main power generation options for Ontario. In this section, the environmental factor is excluded from the objective function in the DUTSF-PSM model. Compared to the power generation targets for different generation technologies in scenario 1, the generation targets for every technology in scenario 2 which are shown in Figure 5 denotes the environmental consideration affect the generation targets allocation significantly especially for the nuclear technology. When the environmental factor is excluded from the objective function, the generation task allocated to nuclear power generation plants are much more than that in scenario 1 which shown in Figure 1.

4.3. Effects of Different Factors on Revenue and Cost of the Power System in Ontario

In the factorial analysis, the low values of the chosen fac-

sults listed in this table indicate that in scenario 1 it is better to

tors (*PRE*, *CEP*, *COE*, and *ECO*) are assumed to be 90% of their high values. PRE denotes the price of power energy. *CEP* represents the cost of primary energy for generation. *COE* and *ECO* are the operation cost of different power generation technologies and carbon emission coefficient for the operation and maintenance stage of power generation technologies respecttively. For the response chosen in the factorial analysis, just the lower bound values of revenue are discussed in this section. According to calculation results achieved by DUTSF-PSM model, the main effect graphs are shown in Figure 6. It is obvious that the effect of *ECO* is the most significant among the chosen four factors.

Table 2. Total CO_2 Emission Amount from Different Types of Power Generation Technologies under Various Levels under $q_s = 0.01$ in Scenario 1

CO_2 emission (Kilotonne)	Period	Low ($h = 1$)	Medium ($h = 2$)	High ($h = 3$)
Hydroelectric ($i = 1$)	$t = 1$	0.00	0.00	0.00
	$t = 2$	0.00	0.00	0.00
	$t = 3$	0.00	0.00	0.00
	$t = 4$	0.00	0.00	0.00
Wind ($i = 2$)	$t = 1$	0.00	0.00	0.00
	$t = 2$	0.00	0.00	0.00
	$t = 3$	0.00	0.00	0.00
	$t = 4$	0.00	0.00	0.00
Solar ($i = 3$)	$t = 1$	0.00	0.00	0.00
	$t = 2$	0.00	0.00	0.00
	$t = 3$	0.00	0.00	0.00
	$t = 4$	0.00	0.00	0.00
Biomass ($i = 4$)	$t = 1$	[17.33, 19.41]	[0.38, 0.42]	[0.13, 0.14]
	$t = 2$	[17.14, 19.20]	[0.73, 0.82]	[0.24, 0.27]
	$t = 3$	[16.96, 19.00]	[0.71, 0.79]	[0.24, 0.26]
	$t = 4$	[17.70, 19.82]	[1.15, 1.28]	[1.15, 1.28]
Nuclear ($i = 5$)	$t = 1$	[3.67, 4.28]	[3.67, 4.28]	[3.67, 4.28]
	$t = 2$	[4.03, 4.70]	[4.03, 4.70]	[4.03, 4.70]
	$t = 3$	[4.43, 5.17]	[4.43, 5.17]	[4.43, 5.17]
	$t = 4$	[4.87, 5.68]	[4.87, 5.68]	[4.87, 5.68]
Natural gas ($i = 6$)	$t = 1$	[4,706.72, 2,571.52]	[135.66, 151.94]	[135.66, 151.94]
	$t = 2$	[5,900.82, 6,608.91]	[278.75, 312.20]	[270.39, 302.83]
	$t = 3$	[5,754.92, 6,445.51]	[255.29, 285.92]	[255.29, 285.92]
	$t = 4$	[5,756.90, 6,447.73]	[265.83, 297.73]	[265.83, 297.73]

5. Conclusions

In this study, a dual-uncertainty two-stage fractional programming power system management (DUTSF-PSM) model was proposed and developed to deal with uncertainties and dual objectives in a power management system through integration of ILP, CCP, MILP, and TSP methods into the framework of a linear fractional programming (LFP) model. The DUTSF-PSM model for power system management in Ontario has several advantages including (1) dealing with the tradeoff problem between two objectives, (2) solving uncertainties expressed as interval and stochastic variables, (3) identifying reasonable power generation target allocation plans, (4) deciding appropriate capacity expansion schemes, (5) reflecting two-stage decisions of the programming, and (6) providing desired plans under different levels of constraint-violation probabilities.

Through the DUTSF-PSM model for power systems in Ontario, the maximal system efficiency based on the least environmental influence under different levels of constraint-violation probabilities can be achieved. Meanwhile, the power generation targets allocation schemes and capacity expansion plans during the whole planning horizon can also be determined by using this model. The results indicate that both hydroelectric and wind power have development potential when the economic and environmental factors are considered in the objective function at the same time.

According to the results of factorial analyses, the carbon emission coefficient (ECO_{it}) of each technology is more significant than that of prices of power generation sales (PRE_t in DUTSF-PSM model), the cost of primary energies (CEP_{jt}), and cost during power generation process (COE_{it}) on the system revenue.

Appendix A

Subscripts

h: energy resource demand level: 1 = low levels, 2 = medium levels, 3 = high levels

i: type of electricity generation technology: 1 = hydroelectric, 2 = wind power, 3 = solar photovoltaics, 4 = bioenergy, 5 = nuclear power, 6 = natural gas-fired power

j: type of primary energy for generation, 1 = biomass, 2 = uranium, 3 = natural gas

m: the capacity expansion option, m = 1, 2, 3, every technology of refining and power generation are provided with three expansion options

t: time period; t = 1: 2016 ~ 2020, t = 2: 2021 ~ 2025, t = 3: 2026 ~ 2030, t = 4: 2031 ~ 2035

Decision variables

XE_{it}: Target electricity by generation technology i in period t (PJ)

XP_{jt}: Target supply of primary energy resource j for power generation in period t (PJ)

YE_{ith}: Excess electricity generated by technology i in period t under level h (PJ)

YP_{jth}: Excess primary energy resource j for generation in period t under level h (PJ)

ZE_{imt}: Binary variable, identifying whether capacity expansion option m for technology i in period t at level h

Parameters

L_{it}: lower availability of renewable energy i in period t (PJ)

U_{it}: upper availability of renewable energy i in period t (PJ)

CE_{imt}: capacity expansion option m for generation technology i in period t (GW)

DM_{th}: electricity demand in period t at level h (PJ)

GE_{ijt}: conversion coefficient from primary energy j to power energy i in period t (PJ/PJ)

RE_i: residual capacity for power generation technology i (GW)

UP_{jt}: availability of primary energy j for generation in period t (PJ)

AET_{th}: annual carbon emission target for power generation system in period t at level h (Ktonnes)

CEE_{imt}: cost factor of capacity expansion option m for power generation technology i in period t (Million \$/GW)

CEP_{jt}: cost factor of primary energy for generation (Million \$/PJ)

COE_{it}: operation cost of power generation technology i in period t (Million \$/PJ)

ECO_{it}: carbon emission coefficient for the operation and maintenance stage of power generation technology i in period t (Kilotonnes/PJ)

PRE_t: price of power energy in period t (Million \$/PJ)

RAE_i: generation efficiency of power generation technology i (PJ/PJ)

p_h: probability levels (i.e., 0.2, 0.6, 0.2 correspond to low, medium and high levels of energy demand, respectively)

$q_{jth,UP}$, $q_{jth,L}$, $q_{jth,U}$: constraint-violation probability for upper bound of primary energy availability, lower bound of power energy availability, upper bound of power energy availability

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