

Financial risk management for new technology integration in energy planning under uncertainty



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HIGHLIGHTS

- Financial risk associated with over or underproduction of electricity is studied.
- A two-stage stochastic model that considers parameter uncertainties is developed.
- The model was applied to a real case to meet projected electricity demand of a fleet of generating stations.
- Incorporation of financial risk resulted in an increase in electricity cost.
- The selection of technologies was the same as that obtained from a deterministic model.

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ABSTRACT

This paper proposes a new methodology to include financial risk management in the framework of two-stage stochastic programming for energy planning under uncertainties in demand and fuel price. A deterministic mixed integer linear programming formulation is extended to a two-stage stochastic programming model in order to take into account random parameters that have discrete and finite probabilistic distributions. This was applied to a case study focusing on planning the capacity supply to meet the projected electricity demand for the fleet of electricity generation stations owned and operated by Ontario Power Generation (OPG). The objective of the proposed mathematical model is to minimize cost subject to environmental constraints. The case study is investigated by considering only existing technologies and also by considering the integration of new technologies that help achieve stricter carbon reduction requirements.

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1. Introduction

Mathematical models that incorporate financial risk management enable decision makers to account for uncertainty in the evaluation and comparison of alternatives. The formulation helps the decision maker to maximize the expected profit and at the same time minimize the financial risk at every profit level. Stochastic programming is a framework for modeling optimization problems that involve uncertainty. The most widely applied stochastic programming models are two-stage linear programs. In two-stage programming, uncertainty is modeled through a finite number of independent scenarios [1]. Scenarios are formed by random

samples taken from the probability distribution of the uncertain parameters as explained by Barbaro and Bagaiewicz [2]. Typical uncertain parameters include prices of raw materials, market demands, process parameters, rate of interest, etc. Recourse is the ability to take corrective action after a random event has taken place [3]. In the planning stage, some decisions are taken before random or uncertain events are known. The remaining decisions are taken only after the uncertain data become known.

Stochastic programming started with several methods to deal with uncertainties such as chance-constrained optimization [4], fuzzy programming [5,6] and the design flexibility method [7]. Some references on two-stage stochastic programming include books by Infanger [8], Kall and Wallace [9], Marti and Kall [10], Uryasev and Pardalos [11], Verweij et al. [12], and Neise [13]. Gothe-Lundgren and Persson [14] discussed a production and scheduling problem focusing on planning and scheduling to select the mode of operation to satisfy the demand while minimizing

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production cost. Recently developed stochastic models included uncertainty and financial risk expanded to the effect of pricing [15–17]. Tolis and Rentizelas [18] implemented a stochastic programming algorithm without recourse to assess the impact of electricity and CO₂ allowance prices in planning expansions in the power sector under several uncertainties. Koltsaklis et al. [19] used mixed integer programming to determine the optimal planning of a power generation system, which included technology and fuel selection and plant allocation to meet required demand while satisfying emission constraints. They investigated the influence of CO₂ emission price as well as other parameters on their results using sensitivity analyses. Zhu et al. used a hybrid mathematical model incorporating mixed integer programming for the optimal planning of regional municipal energy systems [20,21].

Economic needs and the ongoing trend of liberalization of the electricity markets have stimulated the interest of power utilities players to develop operating models and the corresponding mathematical optimization techniques that effectively address the issue of generation and trading of electric/electrical power under uncertainty [22,23]. Eichhorn and Romisch [24] developed a mean-risk optimization model that maximizes revenue and minimizes financial risk. The variables that revealed the stochastic behavior in the model via their uncertainty include electricity demand, and current and future prices. Azaron et al. proposed an approach for designing supply chains considering uncertainties within it [25]. The multi-objective stochastic program involved minimizing both cost and financial risk. Demands, supplies, and prices are the main variables that imposed uncertainty in the model. Stochastic programming has been used extensively in mitigating financial risks and the effect of uncertainties in supply chain design problems [26–29]. It has also been used in refinery operations planning taking into account uncertain demand under the consideration of the cost of unsatisfied demand and overproduction scenarios [30,31].

Deregulated energy markets and the emergence of centralized physical markets in electric power run by independent system operator organizations have resulted in complexities pertaining to managing market risks in both operations and financial aspects [32]. The unit commitment problem deals with the short-term schedule of thermal units in order to supply the electricity demand in an efficient manner. In this type of model, the main decision variables are generators start-ups and shutdowns [33]. In other words, the problem concerns how to most economically schedule the generating units considering the unit economics, physical constraints and incremental transmission losses such that the operator's total commitment to deliver power is met [34].

In classical investment portfolio theory, optimizing the expected return for a specified level of risk is a well-known problem as optimized in the seminal Nobel Prize-winning work of Markowitz [35]. Three dimensions are addressed in this problem: (1) the expected return (or profit and loss P&L) on each instrument in the portfolio; (2) the risk associated with that profit as measured by the variance in the expected profit by Markowitz's mean variance (MV) model or by other alternate measures of risk, such as value at risk (VaR) or conditional value at risk (CVaR); and (3) the quantity of each instrument held. A measure of risk that goes beyond the information revealed by VaR is the expected value of the losses that exceed VaR, thus termed as CVaR [36]. The CVaR mitigates the shortcomings of VaR while possessing the same meaning [37]. Recently, mean-risk models have attracted attention in stochastic programming [38]. Bagajewicz has shown that a solution that minimizes financial risk at cost minimization target also minimizes the expected value of cost of power generation [39]. Gomez-Villalva and Ramos extended a deterministic optimization model into a two-stage stochastic program to account for risk resulting from energy price uncertainty [40].

If improvements in an existing chemical process are not sufficient to meet business needs, then new technologies can be considered. However, the application of a new technology is always perceived as a potential threat. One of the approaches that help alleviate the risk of investment is minimizing the associated financial risk. Based on an extensive review of the literature, there are virtually no studies that incorporate financial risk management within the context of the well-known problem of electric power planning. This paper proposes a new methodology to include financial risk management, which is incorporated by minimizing the CVaR, in the framework of two-stage stochastic programming for energy planning under uncertainties in demands and fuel price. This presents a sophisticated decision making tool to help support better informed investment decisions.

2. Methodology

This paper introduces a new systematic method for screening, identifying, and evaluating technology integration options, which aim at improving the cost-efficiency of a continuous chemical process. The method is organized in four steps (Fig. 1): (1) business case analysis, (2) process improvement without new technologies, (3) process improvement with the incorporation of new technologies, and (4) financial risk management. The first three steps were covered in a prior paper Ahmed et al. [42]. In this paper the fourth step is described in detail and is demonstrated using the same case study. In the previous work, the technologies used in the case study were identified and the feasibility of their integration into

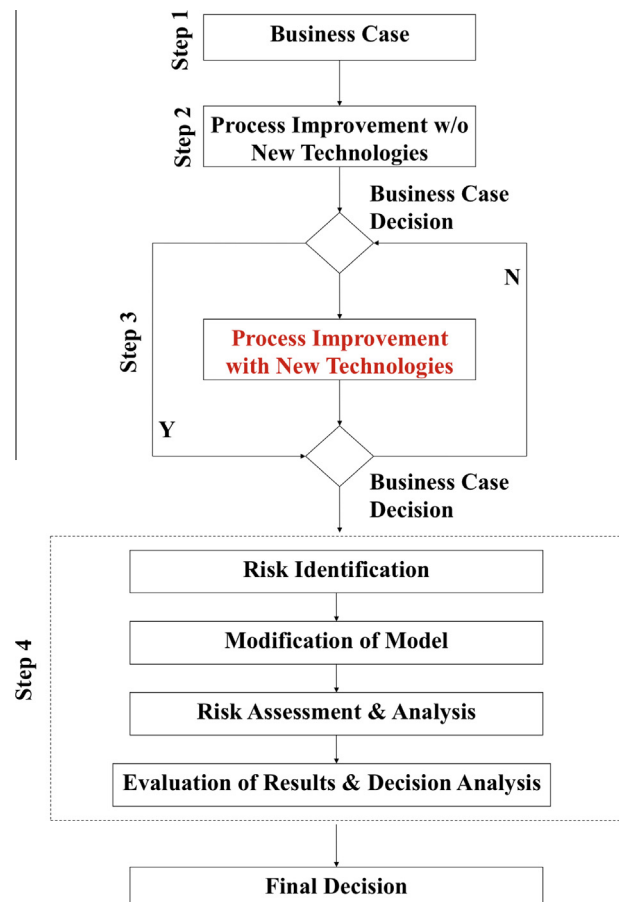


Fig. 1. Summary of steps in the proposed methodology.

the existing process was investigated within a deterministic optimization framework (Appendix A).

The major component of the proposed methodology that influences business decision is financial risk identification and management. The risk is considered for both scenarios where only existing technologies are considered and where new technologies are incorporated. Risk identification involves identifying and categorizing financial risks that could affect the improvement process. The financial risk costs for the alternatives are estimated at various penalty scenarios. The objective is not necessarily to minimize the risks but to evaluate them at various scenarios, so that the decision can be made about capital investment from among many different alternatives. In order to minimize cost of electricity and minimize financial risk at the same time a mathematical formulation, which is called mean-risk model, is introduced. The mean-risk model aims at minimizing the weighted sum of two competing objectives. As weighting factor increases the financial risk management becomes more important while cost minimization turns less important. However, it does not necessarily indicate that the objective function value changes as the weighting factor does.

Sensitivity analysis is also used to assist in evaluating individual risks. It is important to identify the best strategy for each risk then initiate specific actions to implement that strategy. Once there is a clear understanding of risks and their magnitude and options for response, a mitigation strategy could then be introduced. Although mitigation steps are costly and time consuming, they are still preferable to going forward with the unmitigated risk. A problem based on Ontario Power Generation (OPG) energy planning with CO₂ emission considerations is selected as the case study to apply the proposed methodology.

3. Case study

The proposed methodology was tested on a case study based on the electricity sub-sector in Ontario described by Elkamel et al. [41]. The case study was described in detail in a prior work [42]. It focuses on planning the capacity supply to meet the projected electricity demand for the fleet of electric generating stations owned and operated by OPG with a goal to minimize total annualized costs while satisfying CO₂ emission constraints. Approximately 70% of Ontario's electricity supply is provided by OPG. In this case study approximately 28.5% of the generation capacity is generated from fossil fuel combustion plants, and the remaining amount is provided by hydroelectric (27%), nuclear energy (44%), and renewable energy (0.5%) based plants. In 2002, OPG emitted approximately 36.7 million metric tonnes of CO₂ mainly from coal-fired power plants while generating about 115.8 TW h of electricity with total in-service capacity of 22,211 MW. The base load demand was considered constant throughout the year at the nominal level of 13,675 MW [36]. OPG operates approximately 79 electric generating stations which include five coal fired plants, one natural gas generating facility, three nuclear generating plants, sixty-nine hydroelectric generating stations and one small wind turbine facility.

The Kyoto Protocol, developed by the United Nations Framework Convention on Climate Change (UNFCCC), required that Canada reduce its greenhouse gas emissions to 26 million metric tonnes in 2002, which approximately requires 20% reduction of the amount of CO₂ emitted then. Moreover, significantly higher emission constraints were set over the past years, and currently approximately a 60% CO₂ reduction requirement is imposed. Such high CO₂ reduction requirements can only be achieved through the implementation of new technologies. Two technologies were considered, which are natural gas combined cycle and integrated gasification combined cycle with and without carbon capture.

Two options, namely fuel balancing and fuel switching, are used for reducing CO₂ emissions by a certain target. Fuel balancing is the optimal adjustment of the electricity generation of different power plants, and fuel switching involves switching fossil fuel plants from using carbon-intensive fuel (i.e. coal) to less carbon intensive fuel (i.e. natural gas). In this study it is assumed that all of the proposed technologies can operate at full capacity. If the selection or operation of any of the proposed technologies conflict governmental preferences or technological advances, then it will be required for the case study to be resolved.

The results from the deterministic model have shown that achieving the CO₂ emission constraints while minimizing costs affects the configuration of the OPG fleet. Considering only existing technologies the maximum achievable CO₂ percentage reduction was 40%. However, with the implementation of new technologies higher than 60% reduction in CO₂ was achieved at base caseload demand. At 20% CO₂ reduction, which is the emission constraint defined in the case study, the cost of electricity with and without the implementation of new technologies was \$1.40B/year and \$2.11B/year, respectively. The cost of electricity generation from the results of Elkamel et al. [41] at 20% CO₂ reduction target was \$2.95B/year. The considerably lower cost figures that were obtained from the deterministic model in comparison with Elkamel et al. [41] results were due to the unincorporated financial risk and uncertainties.

4. Mathematical model

The mathematical deterministic model that was presented in a prior work [42], and which is summarized in Appendix A of this paper is modified and the formulation of the two-stage stochastic model is presented in detail. The planning problem is characterized by two essential features, which are the uncertainty in the case parameter and the sequence of decisions. Capital investment of various kinds of power plants are decided at the planning stage before the uncertainty is revealed, whereas operating cost and penalty cost are made only after the uncertain parameters become known. The first class of decisions is called first stage decisions. The decisions made after the uncertainty is unveiled are called second stage or recourse decisions.

Financial risk, $Risk(x, \alpha)$, associated with the energy planning case study, is defined as the probability of not meeting a certain target cost minimization level referred to as α as shown in the following equation. The CVaR value is a measure of risk and is defined as the expected cost when the probability that the cost exceeds α is $1 - \beta$ (Eq. (2)).

$$Risk(x, \alpha) = P[Cost(x) > \alpha] \quad (1)$$

$$CVaR = \alpha + \frac{1}{1 - \beta} \sum_s p_s \eta_s \quad (2)$$

With respect to a specified probability level β , α is the lowest amount such that with probability β the cost will not exceed α , and CVaR is the conditional expectation of cost above the amount α . Typically β is pre-selected as 0.95 or 0.99, and in this study the value 0.95 is chosen. In order to minimize the cost of electricity generation and financial risk simultaneously a mathematical formulation a mean-risk model is used (Eq. (3)). Bagajewicz has shown that a solution that minimizes financial risk at a cost minimization target also minimizes the expected value of cost of power generation [34].

$$\min(Cost + \lambda \cdot Risk) \quad (3)$$

where $Cost$ denotes the expected value of cost, and λ is a weighting factor. The mean-risk model aims at minimizing the weighted sum

of two competing objectives. Power plants are divided into the following types: fossil fuel, renewable and nuclear, hydroelectric and wind, and new fossil fuel plants with and without CO₂ capture, which are denoted as f , rn , p and pc , respectively, in the model formulation.

4.1. Objective function

The objective function (Eq. (4)) consists of fixed cost ($FixC$), expected cost ($ExpC$) and financial risk cost (CVaR). The $FixC$ consists of the following: capital investment cost for all power plants and retrofit cost for fossil fuel plants. Furthermore, electricity generation penalty cost (Eq. (5)) and financial risk cost (Eq. (7)) need to be added to obtain an integrated objective function. The stochastic model is modified to also include new technologies. The fixed cost ($FixC$) is adjusted to include the following: capital investment cost for all power plants, retrofit cost for fossil fuel plant, capital cost of new technology power plants, capture cost, and sequestration cost. The operating cost is also adjusted to incorporate new technologies.

$$\text{Min Tot} = \text{FixC}(\text{Capital Cost} + \text{Retrofit Cost}) + \text{ExpC} + \lambda \text{CVaR} \quad (4)$$

$$\text{ExpC} = \sum_s p_s \text{OpC}_s + \sum_s p_s (c^+ z_s^+ + c^- z_s^-) \quad (5)$$

$$\begin{aligned} \text{OpC}_s = & \sum_{f,j} (O_f + \text{Pr}_{j,s} \text{HR}_f) E_f + \sum_{r,n} O_m E_{rn} + \sum_{p,j} (O_p \\ & + \text{Pr}_{j,s} \text{HR}_p) E_p + \sum_{\text{new}} (O_{\text{new}} + \text{Pr}_{j,s} \text{HR}_{\text{new}}) E_{\text{new}} \end{aligned} \quad (6)$$

$$\text{CVaR} = \alpha + \frac{1}{1-\beta} \sum_s p_s \eta_s \quad (7)$$

where the first two terms are $FixC$ first stage decision cost and $ExpC$ is the second stage cost corresponding to scenario s , which has occurrence probability p_s , $s = 1, \dots, NS$. The first stage decision variables are binary variables and continuous variables. The binary variables are used to determine capital investment cost, and the continuous variables are the electricity generation amount for fossil fuel plants, renewable plants and new fossil fuel plants. The variables z_s^+ and z_s^- are recourse variables for the electricity generation amount overproduced and underproduced, respectively, compared to stochastic demand.

4.2. Model constraints

The minimization of the objective functions represented above is subjected to the following constraints. The model constraints are divided into deterministic, stochastic and financial risk.

4.2.1. Financial risk constraint

$$\eta_s \geq \text{FixC} + \text{OpC}_s + c^+ z_s^+ + c^- z_s^- - \alpha \quad (8)$$

For stochastic parts, model constraints deal with uncertain parameters, such as raw material cost and demand corresponding to different scenarios. The aim of the inequality is to choose the first stage decision in an optimal way without anticipation of future outcomes of uncertainties.

4.2.2. Energy balance/demand satisfaction

The total electricity generation ($TotE$) must be equal to or greater than the desired electricity demand, where $Demand$ and $\text{Pr}_{j,s}$ are stochastic parameters for electricity demand and raw material cost for coal and natural gas corresponding to scenario s .

$$\text{Demand}_s = \text{TotE} - z_s^+ + z_s^- \quad (9)$$

$$z_s^+ \geq \text{TotE} - \text{Demand}_s \quad (10)$$

$$z_s^+ \geq 0 \quad (11)$$

$$z_s^- \geq \text{Demand}_s - \text{TotE} \quad (12)$$

$$z_s^- \geq 0 \quad (13)$$

The other stochastic model constraints such as capacity, carbon emission, fuel selection and plant shutdown constraints are the same as those of the deterministic model (Appendix A).

5. Results and discussion

In the cost analysis, $TotCost$ is equal to the summation of $FixC$ and $ExpC$. When λ equals zero, the multi-objective model reduces to a two stage stochastic model without risk management. On the other hand, when λ approaches infinity, the mean risk model only considers risk management, and the total cost minimization is disregarded. The total cost of electricity generation includes capital investment, operational cost and penalty cost for power under-production/over-production. The impact of various penalty values of over and underproduction on the total cost of electricity and financial risk cost was investigated. Two scenarios were considered, where in the first scenario the penalty for excessive generated power (C^+) was taken as \$40/MW h, and the penalty for the shortage of power (C^-) was also taken as \$40/MW h. For the second the penalty values were $C^+ = \$40/\text{MW h}$ and $C^- = \$400/\text{MW h}$.

In all the scenarios investigated when the value of λ increases, the value of total cost increases and the value of financial risk decreases. Through the results it can be observed that the objective function value does not significantly change for all changing weighting factors. A slight difference occurs at certain effective points, which is in agreement with Schultz and Tiedemann's [38] conclusions and results. The results shown are for the case of 6% CO₂ reduction requirement and without the implementation of new technologies. It can be observed in Fig. 2 that for the second scenario the effective weighting factor is 0.6 and the total cost of electricity production is \$3.27B/year, which is 65% higher than the cost of electricity without risk consideration (\$1.98B/year). For the first scenario the effective weighting factor and the total cost of electricity production were 0.5 and \$2.27B/year, respectively. In the second scenario the total cost and financial risk cost are higher because of the higher penalty values. The total and financial risk costs per year increase with an increase in fuel price.

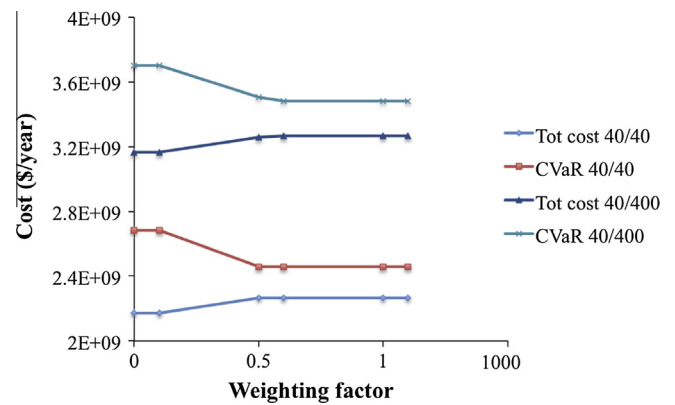


Fig. 2. Total and financial risk costs obtained at various penalty scenarios at 6% CO₂ reduction target using existing technologies.

A sensitivity analysis was conducted where the fuel prices for coal and natural gas were increased by 10%, 50% and 100%. Correspondingly, the total and financial risk costs increased by 1.5%, 3.4% and 6.9%, respectively (Fig. 3). As observed the sensitivity of the objective function value to changes in the fuel price is not considerably high. However, the effect of the fuel prices on the selection of the power generation facilities is significant. For example, high fuel prices will decrease the production capacity of natural gas based plants and will comparatively increase production from nuclear and coal based power plants.

The financial risk associated with the incorporation of new technologies was investigated. The results for the case of penalty costs of $C^+ = \$40/\text{MW h}$ and $C^- = \$400/\text{MW h}$ are shown in Fig. 4. The result exhibit similar trends as those observed for the cases investigated with existing technologies only, where the total cost increases and financial risk cost decreases as the weighting factor is increased. The total cost of electricity was determined to be \$2.33B/year, which is 46% higher than the cost of electricity with new technologies but without risk consideration (\$1.41B/year). However, this cost is 29% lower than the cost of electricity considering existing technologies only with financial risk (\$3.27B/year). The total and financial risk costs increase by approximately 1%, 7% and 13% corresponding to increases in fuel prices of 10%, 50% and 100%, respectively. The results show that an increase in fuel price has a significant impact on the optimized total cost under the consideration of financial risk and uncertainty.

An increase in the CO_2 emission constraint from 6% to 20% resulted in an increase of approximately 5% in the total cost of electricity with the use of existing technologies only where the total cost of electricity was obtained to be \$3.5B/year. However, with the implementation of new technologies and under the consideration of uncertainty and financial risk, an increase in the CO_2 emission constraint from 6% to 20% resulted in less than 1% increase in the total cost of electricity where the total cost of electricity was obtained to be \$2.57B/year (Fig. 5). This is attributed to the higher efficiency, environmental sustainability, and lower operating cost of the new technologies.

For the first and second scenarios the amount of electricity produced ($1.187\text{E}+8$ and $1.286\text{E}+8$, respectively) was approximately equal to the base caseload demand requirement ($1.206\text{E}+8$). However, the difference between the amount of electricity produced in the second scenario and the base caseload demand requirement, the former being higher, can be attributed to the underproduction penalty value, which is considerably high compared to the first scenario (Fig. 6). The distribution of electricity generation among existing and new technologies mostly depends on the CO_2

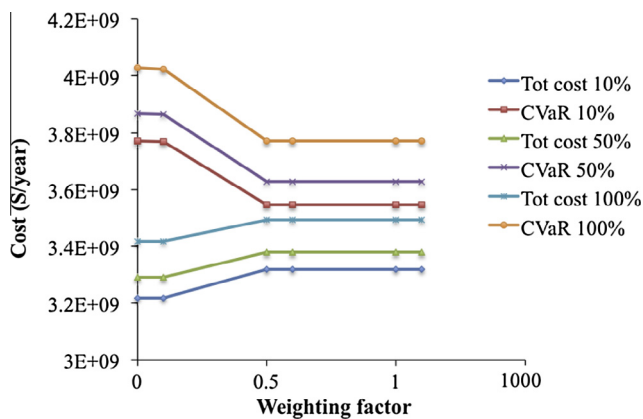


Fig. 3. Sensitivity of total and financial risk costs to changes in fuel prices at 6% CO_2 reduction target using existing technologies.

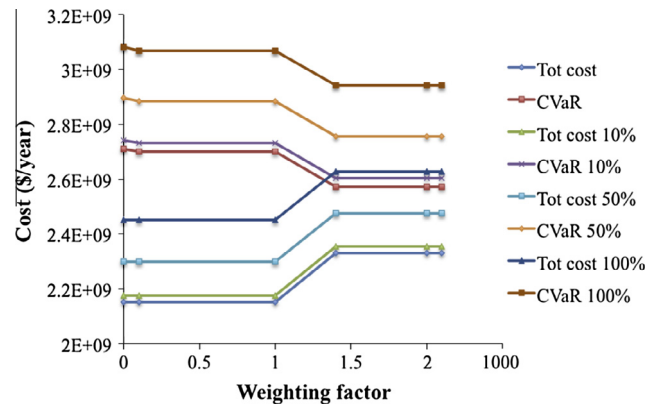


Fig. 4. Total and financial risk costs at 6% CO_2 reduction target with integrated new technologies.

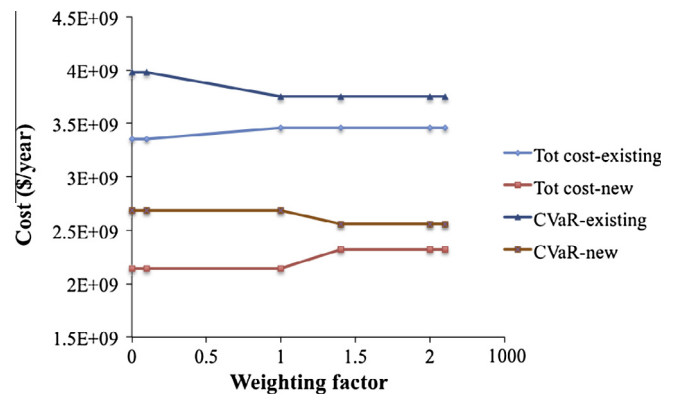


Fig. 5. Total and financial risk costs at 20% CO_2 reduction target using existing and new technologies.

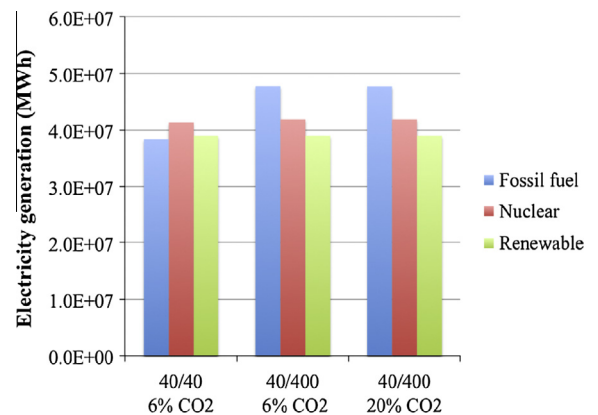


Fig. 6. Distribution of electricity generation among existing technologies at different levels of CO_2 reduction and penalty values.

emission constraint and is sensitive to the prices of fuels (i.e. coal and natural gas).

The results withdrawn from the stochastic model regarding the distribution of electricity generation among the given technologies are comparable to those obtained from the deterministic model [42]. Increasing the production capacity of fossil fuel plants was sufficient to meet the higher production required for the second scenario. This is due to the low CO_2 emission constraint (6%). Fuel switching between coal and natural gas plant is sufficient to meet the higher CO_2 emission constraint (20%). Fuel balancing between

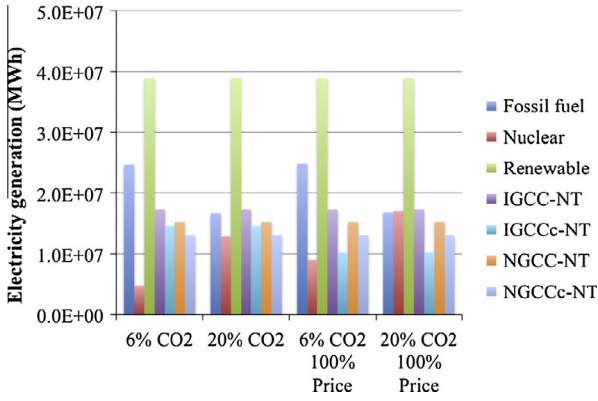


Fig. 7. Distribution of electricity generation among existing and new technologies at $C^+ = \$40/\text{MW h}$ and $C^- = \$400/\text{MW h}$.

fossil fuel based and nuclear plants was more favorable when new technologies were introduced (Fig. 7). It can be observed that the production capacities of nuclear plants increase due to the high costs associated with the carbon capture technologies and the elevated fuel prices.

6. Conclusions

In this paper a stochastic optimization model was presented for the management of the OPG case study in order to demonstrate the applicability of the proposed methodology. Financial risk management was incorporated in the decision making process to select the optimum combination of power generating fleet that minimizes the total cost of electricity generation while meeting production and CO_2 reduction target requirements. The financial risk associated with over or underproduction of electricity was also investigated by outlining several scenarios defined by different penalty values. Changes in the market prices of electricity or of the fuels used to produce electricity are the two main variables that can adversely impact OPG's cash flows. The total cost of electricity at 6% CO_2 reduction target and penalty values of $C^+ = \$40/\text{MW h}$ and $C^- = \$400/\text{MW h}$ using existing technologies was obtained to be \$3.27B/year. However, with the incorporation of new technologies it decreased to \$2.33B/year. The penalty value had a significant effect on the objective function value. For the case of $C^+ = \$40/\text{MW h}$ and $C^- = \$400/\text{MW h}$, the total cost of electricity production was obtained to be \$2.27B/year. Increasing the CO_2 reduction target to 20% for the cases of using existing technologies and incorporating new technologies increased the total cost to \$3.5B/year and \$2.45B/year, respectively. The level of CO_2 reduction and the fuel price, which were investigated through a sensitivity analysis, had the most significant impact on the selection of power generation technologies. The integration of new technologies with existing ones provided a great economic potential as it had a significant effect on reducing the total cost of electricity production.

Appendix A. Deterministic model for new technology integration for energy planning

A.1. Objective function

The objective function consists of minimizing the sum of capital investment cost (\$/MW) for all power plants, retrofit cost (\$/MW) for fossil fuel plant, and operating cost (\$/MW h) for all power plants:

$$\text{Min Tot Cost} = \text{Capital} + \text{Retrofit} + \text{Operating} \quad (\text{A1})$$

$$\text{Capital} = \sum_p F_p A_f \frac{P_{\max}}{T} X_p \quad (\text{A2})$$

$$\text{Retrofit} = \sum_f R_f \frac{F_{\max}}{T} A_f X_{f,ng} \quad (\text{A3})$$

$$\text{Operating} = \sum_{f,j} (O_f + \text{Pr}_j \text{HR}_f) E_f + \sum_m O_m E_m + \sum_{p,j} (O_p + \text{Pr}_j \text{HR}_p) E_p \quad (\text{A4})$$

The variables in the above equations include binary variables and positive variables. Binary variables are used to determine capital investment cost, where $X_{f,j}$ is for fossil fuel plants selection and fuel type decision, j includes two types of fuel, coal and natural gas; $X_{r,n}$ and X_p are to decide whether to build renewable plants or new fossil fuel plants; positive variables are E_f , E_m and E_p , which represent the electricity generation amount for fossil fuel plants, renewable energy plants and new fossil fuel plants process, respectively.

A.2. Constraints

A.2.1. Demand satisfaction

The total electricity generation, TotE , must be equal to or greater than the desired electricity demand.

$$\text{TotE} = \sum_f E_f + \sum_m E_m + \sum_p E_p \quad (\text{A5})$$

$$\text{TotE} = (1 + \text{Ge}) E_d \quad (\text{A6})$$

Ge is gross percentage of electricity demand i.e. 1%, 5%, 10%, 20%, etc. E_d is electricity demand.

A.2.2. Capacity constraints

The following constraints place an upper bound on electricity produced from each plant as well as ensuring that electricity production from fossil fuel plants is zero when no fuel is assigned to the plant.

$$E_{f,j} \leq F_{\max} X_{f,j} \quad (\text{A7})$$

$$E_m \leq R N_{\max} X_m \quad (\text{A8})$$

$$E_p \leq P_{\max} X_p \quad (\text{A9})$$

$$E_{f,j} \geq L_f F_{\max} X_{f,j} \quad (\text{A10})$$

A.2.3. Carbon emission constraint

Here CO_2 emissions must satisfy a CO_2 reduction target. TotCO_2 is total CO_2 emission from all the power plants, and Cre is the CO_2 reduction target. C_{now} is the current amount of CO_2 emission in millions of tonnes per year.

$$\text{TotCO}_2 = \sum_{f,j} C_{f,j} E_{f,j} + \sum_p C_p E_p \quad (\text{A11})$$

$$\text{TotCO}_2 = (1 - \text{Cre}) C_{\text{now}} \quad (\text{A12})$$

A.2.4. Fuel selection and plant shutdown

For each fossil fuel plant, the process is either operating with one chosen fuel or shut down.

$$\sum_j X_{f,j} \leq 1 \quad (\text{A13})$$

For stations that only use natural gas as fuel:

$$X_{ln,ng} = 1 \quad (\text{A14})$$

In is the index of existing fossil fuel stations which chose natural gas. *ng* indicates natural gas.

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