GenCo's Optimal Power Portfolio Selection under Emission Price Risk

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Abstract**—***Carbon markets are a world-wide accepted market mechanism to promote emission reduction. Increasing stress on emission reduction from the power industry has led to a shift in the market mechanism, from free allocation to full auction. Consequent increase in volatility of emission market and its interdependency with electricity market is predominantly affecting the fossil-fuel generation companies (GenCos). For accurate realization of their optimal electricity trading portfolio selection, GenCos need to incorporate cost side uncertainties arising from fuel and emission market volatilities. This paper proposes a novel framework for electricity trading portfolio optimization of a GenCo, considering uncertainties of electricity, fuel and emission markets, to secure its future trading position. This optimization problem is modelled using mean variance portfolio theory, considering spot market and bilateral contracts as electricity trading options. Results show that considering correlation effects of electricity market with emission markets, the proposed framework is capable of improving profit risk trade-off for the portfolio. Positively correlated electricity and emission market prices lead to an increased trading in spot market. In such a situation, the model reflects that spot selling could offer higher risk protection vis-à-vis bilateral contracts, and can prominently help high emission GenCos to minimize their market risks.*

Key words**--**Electricity price uncertainty, emission price uncertainty, fuel price uncertainty, mean variance portfolio theory, risk management.

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I. INTRODUCTION

Fossil fuel (coal, natural gas and oil) fired Generation Companies (GenCos) are dominant electricity producers around the globe. Despite the growth of other power generation sources, future electricity demand growth still necessitates to source a large quantum of its requirement from fossil fuel generation. In electricity markets, such GenCos are dominant suppliers of electricity and responsible for setting market prices. However, carbon emissions from fossil fuel power generation are a major contributor to climate change. With increasing concerns of carbon reduction, emission cost is a new variable that affects GenCos' economic decisions [1].

Carbon markets are evolving as an accepted tool worldwide, to provide cost-efficient solutions for mitigating carbon emissions. European Union Emission Trading Scheme (EU-ETS) is the largest carbon market in the world, covering about 45% of greenhouse gas emissions from the European Union [2]. EU-ETS establishes emission caps for each utility and allows trading of emission permits to fulfill their emission targets. EU-ETS was introduced in phases, which represents compliance periods with continuously stricter emissions reduction targets [3]-[5]. EU-ETS scheme has a considerable impact on a wide spectrum of issues in power industries and electricity markets; such as decision making of generation companies [6], dynamic multi market trading [7-8], self-scheduling [9], unit commitment [10-11], generation technologies selection [12-13], *etc*.

As per Phase III of EU-ETS starting from year 2013, emission permits for the power industry are being allocated via auction mechanism in a competitive market place, instead of the prevailing free allocation mechanism. Power sector has 50% weightage in EU-ETS. Thus, in this phase, the total auction levels would increase by up to 50%, which would significantly boost demand and prices for such credits [4-5]. This will considerably enhance price volatility of such permits. In this context, the importance of understanding carbon price uncertainty becomes quite relevant.

Also, there are complementary studies on carbon price uncertainties, and their influence on electricity market and GenCos [14-16]. Researchers have also reflected the correlation of emission market prices with energy market prices, considering the direct link arising due to overlapping goals [17-19]. Empirical researches suggest that electricity, emission and fuel market (coal, natural gas, *etc*.) prices are usually interdependent and impact of their correlation has been considered for the selection of fuel mix for generation technologies in the power sector [15-16]. However, its impact on economic and trading decisions of fossil fuel GenCos, the prominent carbon emitters, is yet to be considered.

GenCos are involved in trading with different energy and emission markets. They need to procure required fuel and emission permits for electricity production from their respective markets. Uncertainty of fuel and emission permits prices impacts GenCos profit, as it impacts the cost side trading of GenCo. On the revenue side, GenCos sell electricity *via* multiple trading options. These trading options are affected by unpredictable real-time conditions and subject to uncertainty in their prices. With an objective of profit maximization, GenCos strategize their trading to minimize the uncertainty of expected profit [20]. While making electricity trading decisions, power producers strongly consider the revenue side uncertainties and tend to overlook the cost side uncertainties associated with prices of production resources [21-26]. The cost side uncertainties affect energy allocation in electricity trading contract [27-28]. For GenCos' profit maximization, consideration of cost side uncertainties and their interrelation with revenue side contract prices may offer efficient trading strategies with improved risk management. Hence, there is strong motivation for fossil fuel GenCos to consider emission and fuel price uncertainty, along with price uncertainties of electricity market and their inter-dependencies, for deciding its electricity market trading.

This paper incorporates the impact of emission price uncertainty on electricity trading portfolio optimization of a fossil fuel GenCo. The proposed framework considers the uncertainty of revenue and cost side market prices, and models the risk and profit trade-off of a GenCo using mean variance optimization. Further, for electricity trading, a portfolio of pool and bilateral contracts is considered in the suggested framework, involving price uncertainties of emission, fuel and electricity markets. Analysis suggests that a consideration of correlation between purchase prices of production resources and selling prices of electricity impacts optimal portfolio selection. Simulations on practical market data reflect that correlation consideration between emission and electricity market prices enhances trade in spot market. This enhances risk protection vis-à-vis trading in bilateral contracts. The obtained portfolio improves risk management in terms of profit-risk trade-off, when all involved market uncertainties are considered.

II. GenCo's Trading Portfolio Selection

GenCos have multiple options to trade electricity, such as sequential electricity markets, contractual instruments and bilateral contracts. These trading options are affected by unpredictable real-time conditions and are subject to uncertainty in their prices. While aiming to maximize profit, GenCos also intend to minimize the associated uncertainty to secure that profit. GenCos have to manage risk of volatile prices of different electricity trading options to secure the profits [20]. GenCos apply portfolio optimization techniques to manage risk and provide strategies for allocating their generation proportion in different trading contracts, considering its own risk taking desire and risk-return trade-off in prospective markets [21].

This problem considers fossil-fuel GenCo trading strategy in a medium-term time frame (months to year). For such time frame, contract negotiations and planning of trading strategy is done before production as trading and risk hedging decisions are predominant than operational decision making. Considered GenCo plans its future electricity trading in pool and bilateral contracts for a presumed generation. It procures fuel and emission permits from the respective spot markets to meet its electricity production requirements. Thus there are two trading sides, cost side (spot market purchase for emission permits and fuel) and revenue side (spot and bilateral contracts for electricity sale).

The portfolio selection problem in this paper comprehensively considers the uncertainty of electricity, fuel and emission prices. Fuel and emission permit price uncertainty add risk to cost side, while uncertainty in electricity prices makes revenue risky. While developing its electricity trading portfolio for efficient risk management in such a scenario, a GenCo needs to consider cost side risks along with revenue side risk. It allocates its produced output optimally, in available trading options, considering the interdependencies of the three markets involved. Quantum of energy traded in pool and bilateral contract are decision variables for portfolio selection. In this work, markets are assumed to be efficient, competitive and liquid. The GenCo presumes the available generation, considering operational and physical constraints as well as emission caps. This work concentrates on impact of external market uncertainties on GenCo's electricity trading portfolio optimization, and ignores fix-priced long term contracts for fuel and emission markets, which do not have any effect on portfolio risk.

A. Generation Cost

Cost of generation is usually calculated based on the fuel cost required to generate electricity. With the introduction of ETS in the European Union, emission costs are being considered as a component of generator's short-term operational cost. Fossil fuel GenCos are required to purchase emission allowances directly from the market.

Generation cost can be calculated as the sum of fuel and emission cost. The amount of CO_2 emissions are generally related to the quantum of fuel consumed, and can be expressed through incremental heat rate characteristics. Amount of emission for per unit heat rate is calculated based on amount of required fuel and emission factor e_f [10]. Value of e_f depends upon emission type, fuel quality and plant design parameters, which in this case are CO_2 emissions for coal/ natural gas in a stationary combustion system, respectively. It is assumed that GenCo purchases all required emission permits *via* auction mechanism from the emission exchange. Generation is already scheduled as per emission caps, thus each unit of emitted CO_2 from scheduled generation would require emission permit. So, for the total cost calculation of electricity generation, considered fuel cost C^F and emission cost C^E can be expressed in terms of heat rate function $\phi(p)$ which is

$$\phi(p) = a\,p^2 + b\,p + c \tag{1}$$

From heat rate, quantum of fuel required and amount of emission, to generate p_i^G hourly power output during i^{th} trading interval is calculated for the total cost calculation of electricity generation. Considered fuel cost C^F and emission cost C^E can be expressed as:

$$C^F = t\sum_{i=1}^{I}\phi\left(p_i^G\right)\lambda_i^F \tag{2}$$

$$C^E = t\sum_{i=1}^{I}\phi\left(p_i^G\right)e_f\lambda_i^E \tag{3}$$

where total quantum of electricity to be traded among differ contracts is $P_i^G = p_i^G \times t$. i is the index of trading interval for the planning period *I; a, b, c* are heat rate constants for a generating unit, *t* is time in each trading interval (hour); λ^F is the fuel price and λ^E is the emission price. Output power is assumed same for all hours of each trading interval.

B. Revenue from Sale

Fossil fuel GenCo aims to fix its future trading plan for the planning period *I*, for an optimal allocation of its scheduled generation P_i^G, between spot market and bilateral contracts. Revenue generated from the spot market R^S and bilateral contract market R^B are calculated as

$$R^S = t\sum_{i=1}^{I}\lambda_i^S p_i^S \tag{4}$$

$$R^B = t\sum_{i=1}^{I}\lambda_i^B p_i^B \tag{5}$$

Where p_i^S and p_i^B are power traded in spot market and bilateral contract, while $P_i^S = p_i^S \times t$ and $P_i^B = p_i^B \times t$ are quantum of energy traded in spot market and bilateral contract respectively, each for i^{th} trading interval. λ_i^S and λ_i^B are average spot market and bilateral contract prices for duration t in i^{th} trading interval.

C. Total Profit

Total profit π_C of GenCo can be calculated as the difference of revenue generated by selling electricity in different contracts and involved generation cost, as

Profit = (Revenue – Cost)

$$\pi_c = R^S + R^B - C^F - C^E \tag{6}$$

III. Portfolio Optimization using Mean-Variance Theory

A mean-variance approach has been used for portfolio optimization. In Markowitz mean variance theory, the average value of forecast for each trading interval is considered as its expected value and its variance is considered as a risk measure. This theory seeks to reduce the variance of expected profit [29]. This also considers inter-dependencies of uncertain parameters and reflects this correlation impact on portfolio selection.

As per this theory, correlation between different uncertain markets is important for portfolio selection to minimize decision maker's exposure towards risk. Reflection of these correlations provides an efficient portfolio with improved risk management, than a portfolio constructed by ignoring the interactions between securities [30].

A. Expected Profit

The expected profit obtained from (6), for expected values of future prices in different markets, at each trading interval is

$$\pi_c^{Exp} = Exp_{\lambda_i^S, \lambda_i^F, \lambda_i^E \quad \forall i} \left\{ R^S + R^B - C^F - C^E \right\}$$

(7)

Bilateral contract prices are deterministic, *i.e.* known at the time of planning, so expected values are not relevant in their case. Thus, expected profit is given by

$$\pi_c^{Exp} = Exp_{\lambda_i^S, \lambda_i^F, \lambda_i^E \quad \forall i} \left\{ R^S - C^F - C^E \right\} + R^B \tag{8}$$

Using (2) – (4),

$$\pi_C^{E\text{xp}} = t\sum_{i=1}^{I} E\left(\lambda_i^S\right) p_i^S - t\sum_{i=1}^{I} \phi\left(p_i^G\right) E\left(\lambda_i^F\right) - t\sum_{i=1}^{I} \phi\left(p_i^G\right) e_f E\left(\lambda_i^E\right) + t\sum_{i=1}^{I} \lambda_i^B p_i^B \tag{9}$$

Expected values of different market prices, $E\left(\lambda_i^S\right)$, $E\left(\lambda_i^F\right)$ and $E\left(\lambda_i^E\right)$ for each trading interval are calculated as the mean of their respective price vectors, obtained from price forecast or historical data.

B. Uncertainty Model

Revenue obtained from bilateral contract R^B represents zero variance, due to its deterministic nature. However, the uncertainty model involves volatility of electricity, fuel and emission markets and their inter-dependencies by considering variances of individual market's price vectors and their pair-vise covariances respectively. The total risk of expected profit function can be evaluated as variance of profit function and represented as:

$$\pi_c^{Var} = Var_{\lambda_i^S, \lambda_i^F, \lambda_i^E \quad \forall i} \left\{ R^S - C^F - C^E \right\} \tag{10}$$

$$\pi_c^{Var} = Var\left(R^S\right) + Var\left(C^F\right) + Var\left(C^E\right) - 2Cov\left(R^S, C^F\right) - 2Cov\left(R^S, C^E\right) + 2Cov\left(C^F, C^E\right) \tag{11}$$

Variances and covariances evaluated from (2)-(5) are used for calculating variance of total profit as

$$\begin{aligned} \pi_C^{Var} = {} & t^2 \sum_{i=1}^{I} \left(p_i^S\right)^2 Var\left(\lambda_i^S\right) + t^2 \sum_{i=1}^{I} \phi\left(p_i^G\right)^2 Var\left(\lambda_i^F\right) + t^2 \sum_{i=1}^{I} \phi\left(p_i^G\right)^2 e_f^2 \, Var\left(\lambda_i^E\right) \\ & - 2t^2 \sum_{i=1}^{I} \phi\left(p_i^G\right) p_i^S Cov\left(\lambda_i^S, \lambda_i^F\right) - 2t^2 \sum_{i=1}^{I} \phi\left(p_i^G\right) e_f p_i^S Cov\left(\lambda_i^S, \lambda_i^E\right) \\ & + 2t^2 \sum_{i=1}^{I} \phi\left(p_i^G\right)^2 e_f Cov\left(\lambda_i^E, \lambda_i^F\right) \end{aligned} \tag{12}$$

Variance of market prices, $Var\left(\lambda_i^S\right)$, $Var\left(\lambda_i^F\right)$, $Var\left(\lambda_i^E\right)$ and covariance between price vectors of different markets $Cov\left(\lambda_i^S, \lambda_i^F\right)$, $Cov\left(\lambda_i^S, \lambda_i^E\right)$, $Cov\left(\lambda_i^F, \lambda_i^E\right)$ for each trading interval i can be statistically calculated [31]. This covariance represents correlation between two prices, *i.e.* how the two prices are mutually co-related, over each time interval.

GenCo's portfolio is optimized to maximize profit for a minimum risk level. In this multi-objective optimization, weight associated with risk minimization depends upon GenCo's risk taking desire, and is represented by risk weighing factor β. Higher values of β represents a strong risk averse nature of GenCo, which selects a portfolio with low risk. There exists a trade-off between profit and risk. GenCos seeking higher profit have to bear higher risk, or compromise with profit to reduce risk.

This trade-off is incorporated in objective function Z, which aims to maximize profit and minimize the involved risk:

$$max_{P_i^S, P_i^B \quad \forall i} \; Z = \pi_C^{Exp} - \beta \pi_C^{Var} \tag{13}$$

$$P_i^G = P_i^S + P_i^B \quad \forall i \tag{14}$$

$$P_i^S, P_i^B \geq 0 \quad \forall i \tag{15}$$

Final portfolio selection depends upon the scores of objective function Z. Higher values of Z are assigned to portfolios with more attractive trade-off between profit and risk.

C. Impact of Correlation

The following analytical calculation validates the impact of correlation between various market prices, on optimal energy allocation. The objective function Z would be maximized for optimal allocation in risky spot market P^S. Value of P^B is considered from (14) as $P^B = P^G - P^S$.

Considering a fixed total generation, (13) is differentiated to obtain optimum allocation in risky spot market as

$$\frac{\partial Z}{\partial P^S} = t\,Exp\left(\lambda^S\right) - t\lambda_b - 2\beta t^2\left(P^S Var\left(\lambda^S\right) - \phi\left(P^G\right) Cov\left(\lambda^S, \lambda^F\right) - e_f\,\phi\left(P^G\right) Cov\left(\lambda^S, \lambda^E\right)\right) = 0 \quad (16)$$

$$P^S = \frac{Exp\left(\lambda^S\right) - \lambda^B}{2\beta\, t Var\left(\lambda^S\right)} + \frac{\phi\left(P^G\right)}{Var\left(\lambda^S\right)}\left\{Cov\left(\lambda^S, \lambda^F\right) + e_f\, Cov\left(\lambda^S, \lambda^E\right)\right\} \quad (17)$$

$$P^S = \frac{Exp\left(\lambda^S\right) - \lambda^B}{2\beta\, t Var\left(\lambda^S\right)} + \phi\left(P^G\right)\left\{Corr\left(\lambda^S, \lambda^F\right) Var\left(\lambda^F\right) + e_f\, Corr\left(\lambda^S, \lambda^E\right) Var\left(\lambda^E\right)\right\} \quad (18)$$

The optimal risky allocation shown in (18) represents GenCos' electricity allocation in risky spot market. It depends upon the correlation of electricity market prices with fuel and emission market prices, *i.e.* $Corr\left(\lambda^S, \lambda^F\right)$ and $Corr\left(\lambda^S, \lambda^E\right)$ respectively. A positive correlation reflects positively correlated markets that move in the same direction and *vice-versa*. Zero correlation represents that price movement of one market does not help to predict the prices of other markets [31].

Equation (18) represents that positive values of $Corr\left(\lambda^S, \lambda^F\right)$ and $Corr\left(\lambda^S, \lambda^E\right)$ would enhance allocation in risky spot market, as variance is always positive. This represents the fact that a strong correlation between revenue and cost would enhance investment in P^S and because of this, their combined risk π_C^{Var} would reduce. Conversely, negative correlation would reduce allocation in P^S, for improved risk management. However, mutual correlation between emission and fuel markets does not have any impact on portfolio selection, though impacts overall portfolio risk.

IV. Results and Analysis

A fuel fired generation company located at Sweden has been considered for case study (specifications shown in Table I). Two types of fuel, coal and gas, have been considered, each associated with certain emission. Based on the fuel type, emission factors are estimated for CO_2 emissions [32]. The planning period for trading decision making is considered as one month, with each day as trading interval. GenCo plans to sell its total capacity in day-ahead spot market and through bilateral contract. For procuring fuel and emission permits, it directly trades in spot markets of fuel and emission permits. Simulations are performed over several months, and one analysis as example is presented hence.

-- TABLE I --

A. Data

The analysis is performed by using historical data of August month from 2008 to 2012, of electricity from Nordpool [33], of fuel from Nordpool Gas [34] and emission as spot European Union Allowance (EUA) from Bluenext exchange [35]. Expected values of prices for each market, $E\left(\lambda_i^S\right), E\left(\lambda_i^F\right)$, and $E\left(\lambda_i^E\right)$ are considered as the average of price vectors for each trading interval. Coal prices are assumed randomly. Bilateral contract prices are assumed fixed at 40 €/MWh for each considered scenario, with minimum and maximum traded quantity lying between 1200 MWh to 8400 MWh. Each EUA represents a right to emit 1 ton of CO_2 in the atmosphere.

Variance-covariances used in (12), between price vectors of different markets have been calculated in matrix form, for each trading interval, by appropriate functions in MATLAB® [36]. So, for the present case of 31 trading intervals, there exist 31 matrices of size 3×3. These matrices are not shown due to space limitation. To show the effectiveness of market co-movement, day-wise correlations between spot markets of fuel, emission and electricity are shown in Fig. 1. Average correlation matrix between different market prices for entire planning period, each with certain fuel type is represented in Tables II and III. For the considered case, a comparatively higher correlation between market prices of electricity and emission permits, than that between electricity prices and fuel prices, has been observed. This may vary depending upon considered data. However, it should be noted here that evolving market scenario addressed in this paper, *i.e.* a complete auction based purchase mechanism for power sector, would lead to a higher correlation between electricity and emission prices. The diagonal elements in Tables II and III have unity values to represent correlation between same markets.

-- Figure 1 --

-- TABLE II --

-- TABLE III --

B. Scenario Consideration

This work concentrates on the impact of price uncertainties of external markets on electricity market trading decision making. For analysis, three scenarios are considered sequentially, involving uncertainties of fuel and emission markets on trading of both types of GenCos, however fuel and emission prices are considered in all scenarios for profit calculation. In Scenario I, only electricity market uncertainty is considered taking fuel emission prices as deterministic. In Scenario II, fuel price uncertainty is considered along with electricity market uncertainty. In Scenario III, price uncertainties of all involved markets are considered.

C. Analysis and Observation

Gas and coal fired GenCos are analyzed individually for portfolio selection. Generation cost and revenue corresponding to different contracts are calculated using (1)-(5) for each trading interval, based on specification shown in Table I and prices of different markets. Overall expected profit and involved risk has been calculated using (9) and (12), considering all trading alternatives. On the basis of total expected profit and involved risk, objective function (13), subject to constraint (14), is optimized. This MINLP optimization problem has been solved by commercially available software GAMS, on its solver SBB-CONOPT3 [37].

Optimization is performed for various values of β, wherein each value of β produces an efficient portfolio, in terms of profit and standard deviation. The contour of these portfolios is known as efficient frontier. β represents risk averse nature of GenCo. Efficient frontier reflects the fact that with increasing risk averseness, both standard deviation and expected profit of portfolio decrease. It means that high profit seeking GenCo has to bear higher risk and a low risk seeking GenCo has to compromise with profit. This signifies the trade-off between profit and risk that a GenCo has to select, reflecting its risk bearing desire, as decided by β.

1) Impact on Coal-Fired GenCos

For all three considered scenarios, optimum portfolio is obtained for coal fired GenCo, and is shown as efficient frontiers in Fig. 2. Each frontier has a different profit-risk profile for similar values of β. In comparison to other scenarios, Scenario I does not consider cost side uncertainties and the resultant efficient frontier represents highest risk and lowest expected profit for similar values of β. However with sequential integration of uncertainties associated with cost side markets, *i.e.* fuel and emission in Scenario II and III respectively, efficient frontiers reflect comparatively higher profits and lower risks. This signifies continuously improving trade-off in terms of profit and risk, for similar values of β. This happens due to positive correlation of cost side markets with electricity market prices. When prices of electricity spot market commoves with cost side markets, variations of electricity market can be compensated by variations of generation cost. By this, a GenCo would feel more secure, and would invest more in that trade. Thus with a consideration of cost side uncertainties, allocation in spot market increases as shown in Fig. 3.

--- Figure 2 ---

--- Figure 3 ---

Allocation in spot market depends upon its prices for considered trading interval and involved uncertainties. Fig. 3 shows variations in spot market trading allocation for different risk aversion levels, and for each trading interval in (a), (b) and (c) and for entire planning period in (d). For initial trading days, spot market allocation is low due to low market prices, while for remaining days, it is observed to decrease with increasing values of risk aversion level of GenCo. In Fig. 3, it is to be noted in (b) that for days 8-10, 16, 23, 28-31, *etc.* when coal prices are strongly correlated with electricity market prices, decrement in allocation for spot market is slow as compared to Scenario I. However, with a consideration of emission price uncertainty, and due to strong correlation between prices of emission and electricity markets, more energy is allocated to the spot market, for same risk aversion levels. This can be visualised for Days 2, 8-10, 16, 19, 22-24, 28-31, *etc*. by comparing Fig. 3 (b) and (c), and indicated in Section III/C at (18) as well. It represents that change in cost is compensated by change in revenue. The portfolio risk is better controlled with positively correlated revenue and cost, which can be achieved by higher allocation in spot market. Comparative allocation in electricity markets (spot and bilateral) has been analysed for all considered scenarios in Fig. 3 (d).

2) Impact on Gas-Fired GenCos

As compared to coal fired GenCos, emission from gas fired GenCos is comparatively low, and so emission cost and its uncertainty exert less impact on its trading decisions. This difference can be visualized by comparing Figs. 3 (d) and 5 (d), where the latter shows a relatively small allocation shift in electricity market for Scenario III. Gas prices are more volatile than coal market prices and comparatively represent a weak correlation with electricity market prices (Fig. 1 and Table III). Thus consideration of fuel market uncertainty in this case enhances portfolio uncertainty for similar risk aversion levels, as shown in Fig. 4. However, this improves profit profile as eventually prices of gas market and electricity spot market are correlated, which leads to relatively higher allocation in spot market for Scenario II *vis-à-vis* Scenario I. In Scenario III, consideration of emission price uncertainty reduces portfolio risk and enhances profit by higher allocation in spot market. A positive correlation between emission and electricity markets could offer risk protection here as well. For the same risk aversion level, more electric energy can be allocated to spot market, when emission prices are considered uncertain, as compared to other scenarios. This can be visualized by analyzing Figs. 4 and 5 for all trading intervals and over the total planning period.

--- Figure 4 ---

--- Figure 5 ---

3) Impact of Bilateral Contract Prices

To understand the impact of varying bilateral contract prices on overall risk, additional simulations have been performed at different bilateral price levels. Three bilateral contract prices of 36 €/MWh, 38 €/MWh and 40 €/MWh are considered, for coal fired GenCo and data given in Section IV (A), with and without considerations of emission price uncertainty. Fig. 6 shows efficient frontier obtained for these bilateral prices, considering Scenarios II and III. The bold plots represent efficient frontiers considering emission prices uncertainty, as for Scenario III. Left-side shifting of frontiers represents reduction in portfolio risk. It can be observed that a relative shift in efficient frontier due to consideration of emission uncertainty is less for high bilateral contract prices. This reflects decreasing impact of emission price uncertainty, with increasing bilateral contract prices. This is because with the involvement of cost side uncertainty, cost side risk cannot be hedged by trading in bilateral contracts. Conversely, correlated trades may compensate price movement of cost side in case of electricity spot and emission markets, which however is non-existent for bilateral contracts. This indicates that selling production through bilateral contracts may not necessarily help to reduce profit risk, whereas spot selling could offer overall risk protection.

--- Figure 6 ---

Finally, it can be concluded that correlation of emission market prices with electricity prices provides opportunity for improved risk management, by altering electricity trading schedules. Further, overall risk of cost and revenue side can be reduced for a fossil fuel GenCo by selling more in spot market, because of usual positive correlation between prices of involved markets. For appropriate portfolio selection intended to manage secure profit, consideration of all involved uncertainties is essentially important. However, involvement of external market uncertainties enhances overall profit risk, but its correlation with electricity market prices would help the decision maker to select most appropriate portfolio, which contains reduced risk and higher profits. Hence, correlation considerations are important for actual realization of trading strategy. When these prices were negatively correlated, energy allocation in risk free bilateral contract would increase, and that in spot market would decrease. High impact of emission price uncertainty and its strong correlation with electricity market could help to reduce overall portfolio risk of high-emission coal fired GenCos. Gas fired GenCo offers similar impact, however individual uncertainty of gas prices is higher than coal market, and effect of emission prices is less for low emitting GenCos. Thus portfolio uncertainty does not improve much.

V. Conclusion

In the upcoming power sector scenario, GenCo's emission cost is directly influenced by emission permit prices and their volatility. Electricity generation cost of high-emission GenCos become uncertain due to volatility of fuel and emission permit prices. Such cost side uncertainties alter electricity trading portfolio decisions of emitting GenCos, and underscore the significance to manage overall risk of securing expected profit. Mean variance portfolio theory offers optimal electricity trading portfolio for such GenCos, considering co-movement of cost and revenue sides.

The results indicate that usual correlation with fuel, emission and electricity markets can improve the portfolio in terms of profit risk trade-off. However, uncertainty of cost side market enhances portfolio risk. This can however be used to mitigate overall portfolio risk by considering their correlation with electricity market prices. Strong correlation of emission market prices with electricity spot prices leads to an increased trading in spot market, thereby reducing portfolio risk. This situation reflects that a higher allocation in spot market may hedge risk, as the risk of price change in emission market is compensated by a corresponding price change in spot market. Such correlation consideration may help the GenCo to reduce overall portfolio risk by trading in spot market, which otherwise may not be possible with bilateral contracts. A comparative analysis of coal and gas fired GenCos represents that emission price uncertainty has a higher impact on trading of high emission GenCos, however improves profit risk trade-off for both types of GenCos. The presented work can be extended for portfolio optimization involving multiple trading options, with their individual returns and risk characteristics.

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TABLE I

GENERATING UNIT SPECIFICATIONS

Fuel Type	Gas	Coal
Generation capacity	400 MW	400 MW
Quadratic heat-rate coefficient	0.000115MBtu/MW^2	0.00037MBtu/MW^2
Linear heat-rate coefficient	4.515MBtu/MW	4.76MBtu/MW
No-load heat-rate coefficient	185MBtu	683.91MBtu

Emission Factor	0.054 tCO_2/MBtu	0.0955 tCO_2/MBtu

TABLE II

CORRELATION BETWEEN MARKETS WITH FUEL TYPE COAL

	Electricity	*Coal*	*EUA*
Electricity	1	0.6821	0.8871
Coal	0.6821	1	0.5875
EUA	0.8871	0.5875	1

TABLE III

CORRELATION BETWEEN MARKET PRICES WITH FUEL TYPE GAS

	Electricity	*Gas*	*EUA*
Electricity	1	0.3206	0.8871
Gas	0.3206	1	0.0914
EUA	0.8871	0.0914	1

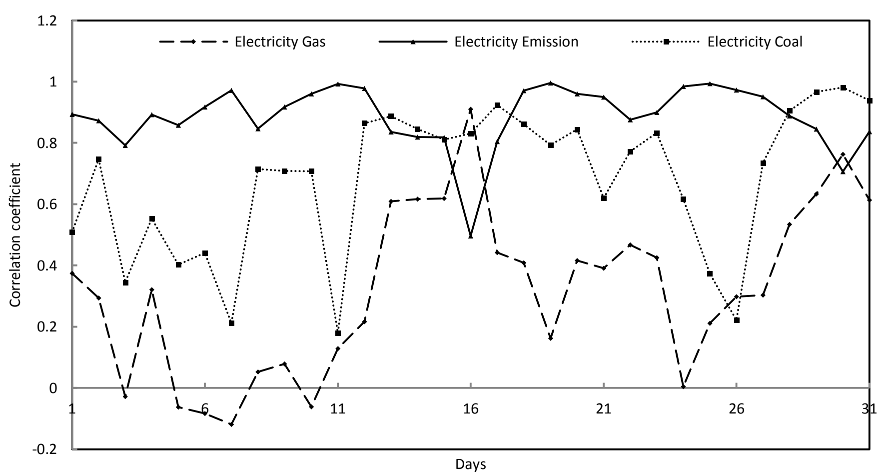


Fig. 1 Correlation of electricity market with other markets for each trading interval

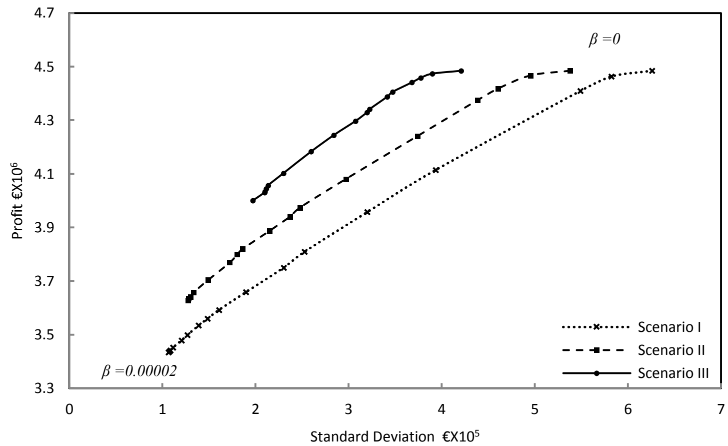
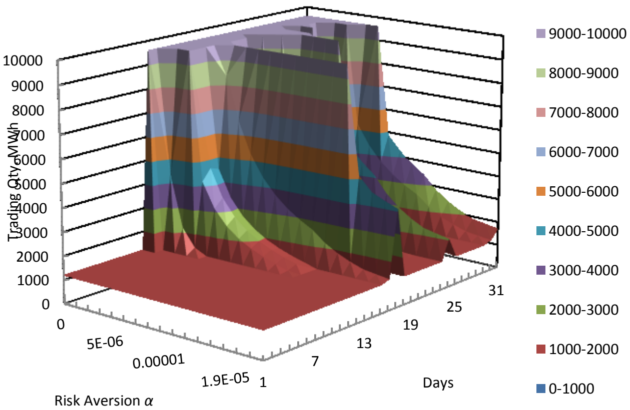
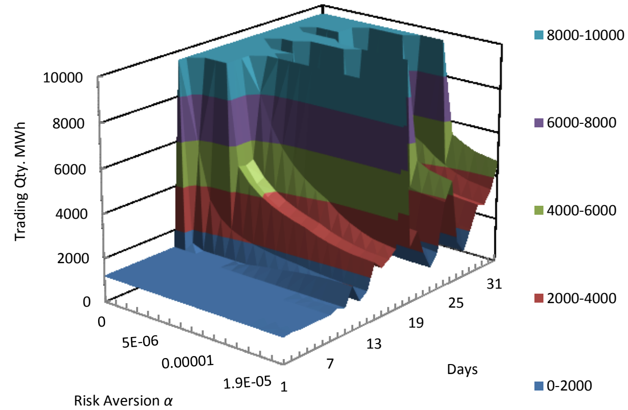


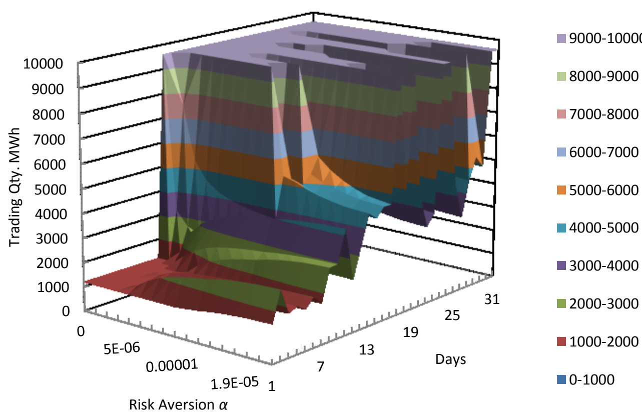
Fig. 2 Efficient frontiers for Coal fired GenCos



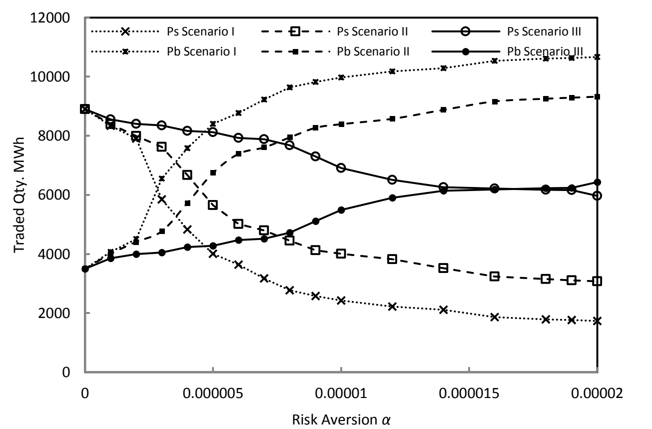
(a) Spot market for each trading interval in Scenario I



(b) Spot market for each trading interval in Scenario II



(c) Spot market for each trading interval in Scenario II



(d) Spot market and bilateral contract for total planning period

Fig. 3 Optimal energy allocation for coal fired power plant

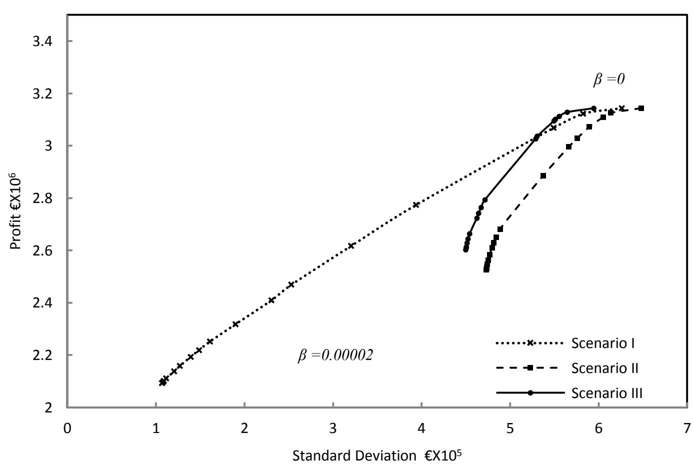
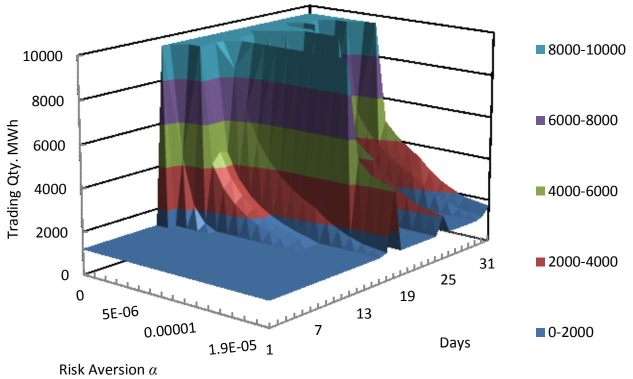
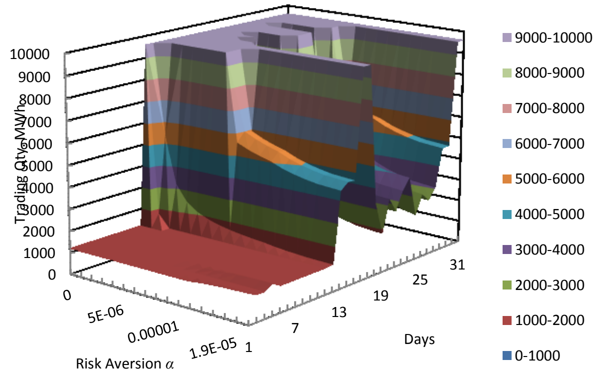


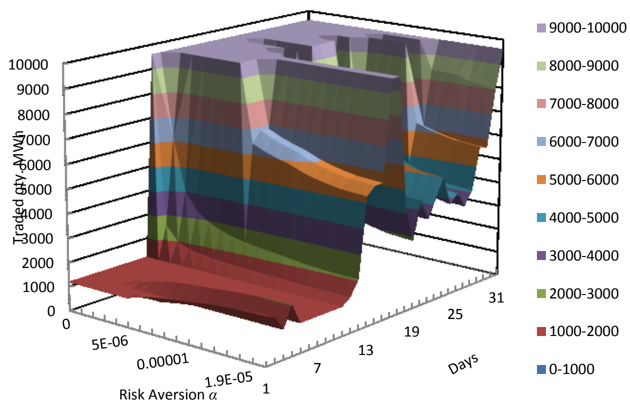
Fig. 4 Efficient frontiers for gas fired GenCos



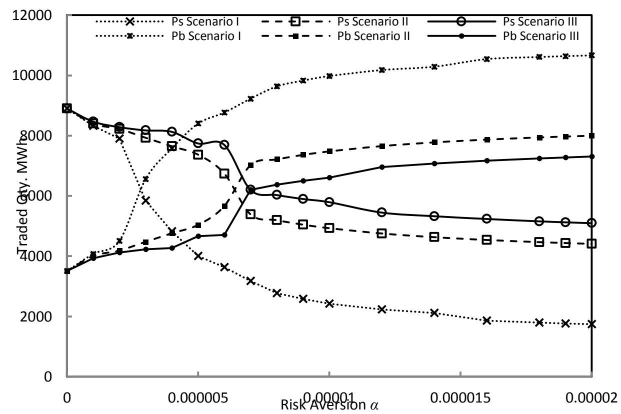
(a) Spot market for each trading interval Scenario I



(b) Spot market for each trading interval Scenario II



(c) Spot market for each trading interval Scenario II



(d) Spot market and bilateral contract for total planning period

Fig. 5 Optimal energy allocation for gas fired power plant

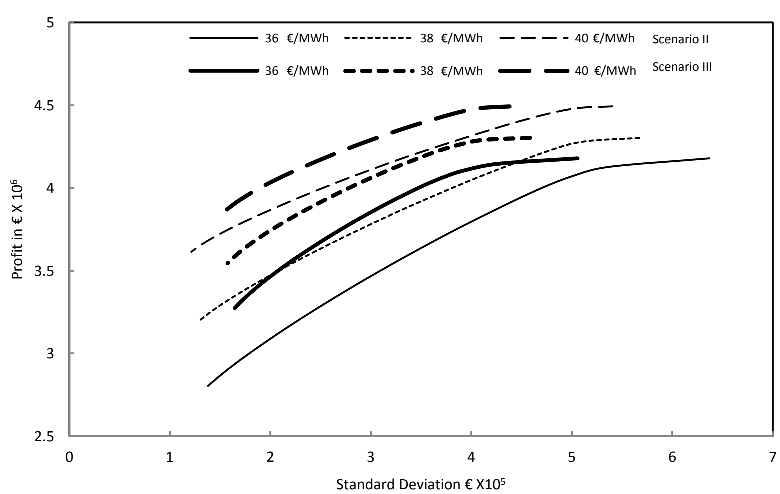


Fig. 6. Efficient frontiers for various bilateral contract prices