CO2 volatility impact on energy portfolio choice: a fully stochastic LCOE theory analysis

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Abstract

Market based pricing of CO2 was designed to control CO2 emissions by means of the price level, since high CO2 price levels discourage emissions. In this paper, it will be shown that the level of uncertainty on CO2 market prices, i.e. the volatility of CO2 prices itself, has a strong influence not only on generation portfolio risk management but also on CO2 emissions abatement. A reduction of emissions can be obtained when rational power generation capacity investors decide that the capacity expansion cost risk induced jointly by CO2 volatility and fossil fuels prices volatility can be efficiently hedged adding to otherwise fossil fuel portfolios some nuclear power as a carbon free asset. This intriguing effect will be discussed using a recently introduced economic analysis tool, called stochastic LCOE theory. The stochastic LCOE theory used here was designed to investigate diversification effects on energy portfolios. In previous papers this theory was used to study diversification effects on portfolios composed of carbon risky fossil technologies and a carbon risk-free nuclear technology in a risk-reward trade-off frame. In this paper the stochastic LCOE theory will be extended to include uncertainty about nuclear power plant construction times, i.e. considering nuclear risky as well, this being the main uncertainty source of financial risk in nuclear technology. Two measures of risk will be used, standard deviation and CVaR deviation, to derive efficient frontiers for generation portfolios. Frontier portfolios will be analyzed in their implications on emissions control.

Keywords: Levelized cost of electricity, nuclear power, risk and deviation measures.

JEL Code: Q40,G31,G32,L94,M21.

1 Introduction

Carbon markets and carbon prices were introduced to help limit CO2 production in order to mitigate global warming in a market oriented way. In this sense, CO2 price signals force electricity producers to internalize emission damages, and to share with consumers internalized environmental costs [1], [2]. In addition, producers must face and manage uncertainty about future CO2 prices when planning capacity expansion. CO2 price volatility itself, besides CO2 price levels, in addition to volatility of fossil fuels prices, can have a strong influence on the environment through power production decisions.

In this paper, we will show an intriguing effect of CO2 price volatility on optimal decisions of electricity producers who have to decide about the percentage of different fuel components (coal and gas) in their mix of generation assets, i.e. about how to diversify their energy portfolios. We will show that rational electricity producers should include a nuclear asset (i.e. a CO2-free source) in their energy portfolios of baseload electricity production in order to minimize the adverse joint impact of CO2 and fossil fuels prices volatility on costs, thus reducing the CO2 emitting component of their power portfolios. Under this perspective, the existence of CO2 volatility can be beneficial to the environment.

To this goal, we will use a recently introduced economic analysis tool designed to investigate diversification effects on energy portfolios composed of fossil and nuclear components for the baseload production, called stochastic LCOE (Levelized Cost of Electricity) theory [3], [4], which extends the classical (deterministic) LCOE theory. This approach helps a better understanding of the consequences to the inevitable trade-off between the cost of production and its uncertainty on capacity planning risk assessment and management.

In [3] and [4], we modeled uncertainty as due to coal, gas and CO2 prices only, so that in such a risk model nuclear technology cannot be considered as a financially risky asset. Yet, nuclear power is perceived by public opinion as generically dangerous, raising concerns and hostility to construction of new plants. Consequently, when planning and financially assessing any capacity expansion which adds nuclear generation to other generation assets, nuclear should be treated as a risky asset, because hostility can slow down and make uncertain construction times, and in turn construction times have a strong impact on the generation costs. Thus, to make the analysis presented in this paper as much robust as possible, we will take into consideration a further source of uncertainty on electricity production costs, namely, the time it takes to build a nuclear power plant. Uncertainty on construction times makes the nuclear technology risky like coal and gas technologies, an effect not included in previous publications (hence the specification 'fully stochastic' in the title). Thus in our new risk model we assume four independent sources of risk, namely coal, gas, CO2 prices and nuclear plant construction times, and we make the nuclear LCOE risky but independent from coal and gas LCOEs, as it will be explained in the paper[1]. On the contrary, gas and coal LCOEs will be dependent on each other, like in the our previous work. Moreover, due to independence between the fossil fuels stochastic LCOEs and the nuclear stochastic LCOE, the nuclear source can still be used as a hedging asset to reduce both the volatility of electricity generation costs in a well diversified power portfolio. It should be noticed that elsewhere it was pointed out that 'nuclear power can reduce emissions and maintain a strong economy' [5], [6], being this a first direct way of reducing emissions by means of nuclear technology. In this paper, we're going to illustrate a further more subtle channel which can be exploited to reduce emissions, which still links nuclear to CO2. It will be in facts shown that, in the presence of CO2 volatility, rational choice pushes toward a larger share of low carbon fuels. If nuclear is part of an energy portfolio, this beneficial effect of CO2 volatility will be enhanced.

In the paper we will determine optimal power generation portfolios and efficient frontiers using two different risk measures, namely standard deviation and Conditional Value at Risk Deviation (CVaRD), as a standard methodology developed in [4]. The necessity to use such an unconventional risk measure like CVaRD is due to the fact that, in general, LCOE distributions are not Gaussian, having asymmetric long thick tails [7], and are positively definite. Value at Risk (VaR) and Conditional Value at Risk (CVaR) could be chosen at a first thought as the obvious candidates for an extension beyond standard deviation [8]. Yet, it turns out that they are not the best choice for this problem, because VaR and CVaR actually are 'risk measures', and not 'dispersion measures' or 'deviation measures' unlike standard deviation or CVaRD [9], and cannot capture that risk attitude on which our analysis is based.

Four are therefore the main contributions of this paper to the existing literature. They can emerge in the context of our stochastic LCOE theory only. First, the stochastic LCOE theory is extended to include the main source of financial risk in nuclear power generation,

[1] In facts, only in extreme situations, when for example fossil fuel prices skyrocket and permanently stay high so that public opinion accepts nuclear plants and does not delay their construction, nuclear LCOE could show some weak correlation with coal and gas LCOE.

that is the uncertainty of construction times. Second, and more importantly, it is shown that CO2 emissions reduction can be obtained as a reaction to the CO2 volatility impact on well diversified power portfolios, possibly including nuclear. Third, we propose a data-driven empirical analysis and a risk-return approach to energy portfolios, which cannot avoid the use of somewhat sophisticated deviation measures, because of the structure of the assumed risk model. As not abstract applications of the method we will discuss two case studies in detail, with two CO2 volatility scenarios, using prices and technical parameters from US data [10], working out related efficient frontiers and optimal generation portfolios. Fourth, the amount of emission reduction can be numerically quantified, i.e. we show that the combined effect of fossil fuels prices volatility and CO2 price volatility controls CO2 emissions to an extent that can be quantified.

Finally, notice that this theory can be used both from an investor's point of view - which need to hedge perspective cost fluctuations and extreme cost events when expanding capacity, and from a policy maker's point of view - which needs to assess system wide costs (including environmental costs) and risks, and to guide investors by means of tuned up CO2 price mechanisms.

The plan of the paper is the following. After this Introduction, in Sec.2 we review the stochastic LCOE theory, showing that single-fossil fuel technologies can be seen as risky assets correlated among each other through CO2 volatility, so that an energy portfolio diversified in technologies contains correlated risky assets. This will give us the possibility to apply Markowitz portfolio analysis [11] to capacity planning optimization. In Sec.3 we discuss the four financial risk sources taken into account in our setting and we illustrate the models used in our analysis, namely the risk models associated to the stochastic dynamics of coal and gas market prices, to the stochastic dynamics of CO2 prices, and regarding the nuclear source, the model to describe uncertainty about the construction time of nuclear power plants. More specifically, as proposed in [4], we discuss how to use a mean-reverting jump-diffusion process to model gas prices, a geometric Brownian motion to model coal prices, and a geometric Brownian motion to model CO2 prices, for two different interesting

CO_2 volatility scenarios in order to highlight CO_2 indirect effects on single-fuel LCOEs cross-correlation. We also discuss in detail how to model the uncertainty about construction time of nuclear plants, by using first a normal distribution then a beta-binomial distribution, with fitting parameters obtained from a carefully collected market dataset containing data on all operating reactors that were built and connected to the grid in the last twenty years (1995-2014) all around the world. In this model, nuclear LCOE will turn out independent from the (mutually dependent) fossil fuel LCOEs. In Sec.4 we discuss and motivate our choice among available risk and deviation measures and highlight the properties of deviation measures. Then, using the proposed model, we draw and discuss efficient frontiers of power generation portfolios under standard deviation and CVaRD. We discuss in detail portfolio choices optimal under such measures, thus putting in evidence the important role of a zero-covariance nuclear asset in this problem. We show quantitatively how CVaRD improves, w.r.t. the theory proposed by Mari [3], the shape of the portfolios LCOE distribution when aversion to asymmetric tail risk is considered, and qualitatively how emissions are reduced under this (purely economic) choice scheme. In Sec.5 we conclude. Appendices A and B include all the data used in the simulation analysis necessary to reproduce the results derived and discussed in the paper.

2 The Stochastic LCOE Theory

Stochastic LCOE can be introduced as an extension of the classical deterministic LCOE theory, which we recap in the following. Consider a project of an electricity generating plant, seen as a cash flow stream on a yearly timetable $\{n|n = -N, \ldots, 0, \ldots, M\}$ for which the integer $n = -N < 0$ is the construction starting time, $n = 0$ is at once

- the end of construction time,
- the evaluation time,
- the operations starting time,

and $M \geq 1$ is the end of operations time (see Fig.1).

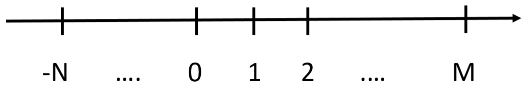

Figure 1: Project timeline.

Classically, the LCOE (LC in short) is defined as that nonnegative price $P^{\mathrm{LC,x}}$ (assumed constant in time, and expressed in real money units) of a unit of the electricity (1 MWh) produced by a specific generation technology x which makes the present value (PV) of expected revenues from electricity sales equal to the present value of all the expected costs met during the plant life-cycle, as investment costs, operating costs, incremental capital costs, decommissioning costs, income taxes and carbon charges when due [12]. The LCOE represents the generating costs at the plant level (busbar costs) and does't include transmission and distribution costs and all possible network infrastructures adjustments. To determine the LCOE, the PV is computed by using a discount rate that must provide equity investors the adequate return for the assumed risk. In general, this return is quantified by the Weighted Average Cost of Capital (WACC) which accounts for the possibility that a given project can be financed by a mix of equity and debt [13]. Assessing the LCOE through the WACC specification allows one to include the level of risk perceived by investors. The LCOE is therefore a break-even reference unitary cost, and, given a set of technologies, it allows one to compare to each other the costs of electricity generation when investing in each of these technologies. Furthermore, it can be used for determining the aggregated cost of electricity in the case of a portfolio of technologies. Specifically, this paper will focus on LCOEs for the baseload production of electricity obtained from two fossil fuel technologies, coal and natural gas, and from the nuclear technology.

The analytic form of the LCOE for a specific technology x is obtained equating at $n = 0$ the present values of expected revenues and costs. Once this equation is solved the LCOE can be cast in the following way:

$$P^{\mathrm{LC,x}} = \frac{\sum_{n=1}^{M} C_n^x F_{0,n}}{Q^x \sum_{n=1}^{M} (1+i)^{n-n_b} F_{0,n}} + \frac{I_0^x - T_c \sum_{n=1}^{M} dep_n^x F_{0,n}}{(1-T_c) Q^x \sum_{n=1}^{M} (1+i)^{n-n_b} F_{0,n}}. \tag{1}$$

A derivation of Eq.(1) can be found in [4]. Q_n^x denotes the expected amount of electricity produced during each period and it will be assumed constant (as $Q^x = CW^x \times 8760 \times CF^x$, where CW^x is the nominal capacity of the plant and CF^x the Capacity Factor of that plant), i is the expected yearly inflation rate, n_b refers to the base year used to compute real prices from nominal prices, and $F_{0,n} = 1/(1 + WACC)^n$ is the discounting factor in the WACC approach, where WACC is kept constant for the whole life of the project. The technology label x can take the values 'co' (coal), 'ga' (gas) and 'nu' (nuclear). In the first term of the r.h.s. of Eq.(1), C_n^x denotes expected nominal operating expenses which are incurred throughout the operational life of the plant including fixed and variable operation and maintenance (O&M) costs, fuel costs (not included in the variable O&M costs), radioactive wastes management costs and set-aside decommissioning funds in the case of nuclear energy. Fixed and variable O&M costs and fuel costs are computed using real escalation rates. With regard to fossil fuels, costs have to include CO2 costs, or carbon taxes, or abatement expenses. In the second term of the r.h.s., T_c is the tax rate, I_0^x is the pre-operations nominal investment, starting at $n = -N$ and ending at $n = 0$, but computed as a lump sum [2], and dep_n^x is the fiscal depreciation.

Eq.(1) is valid for a single-technology project. For a multi-technology project, i.e. a portfolio of technologies, the total price P^{LC} is the sum over the technology index x

$$P^{\text{LC,w}} = \sum_x P^{\text{LC,x}} \frac{Q^x}{Q^{\text{TOT}}} = \sum_x w^x P^{\text{LC,x}}, \tag{4}$$

where $Q^{\text{TOT}} = \sum_x Q^x$, and

$$w^x = \frac{Q^x}{Q^{\text{TOT}}} \tag{5}$$

[2] I_0^x is computed in the following way. Denoting by $\bar{O}_n^x$ the real amount of the overnight cost allocated to year n (again with reference to Fig. 1), the nominal amount O_n^x at year n can be expressed as,

$$O_n^x = (1+i)^{n-n_b} \bar{O}_n^x \qquad n = -N, \cdots, -1, 0. \tag{2}$$

Then, within the WACC approach,

$$I_0^x = O_{-N}^x (1 + WACC)^N + \cdots + O_{-1}^x (1 + WACC) + O_0^x. \tag{3}$$

is the weight of technology x in the portfolio. When Q^x is expressed in MWh and prices are in dollars, P^{LC} is expressed in real dollars per MWh.

Two remarks can be interesting. First, although the LCOE approach has been used as an alternative to more traditional evaluation techniques based on Net Present Value (NPV), it should be noticed that the maximization of the NPV per unit of output as a choice criterion for selecting in the deterministic frame optimal portfolios, is anyway equivalent to the minimization of the LCOE[3]. Second, the equation that implicitly defines the LCOE as shown in Eq.(1) is used also in other contexts[4]

In this paper we will study LCOEs for the US market, like in [4], using data from Tab.A.1 (shown in Appendix A), which details all necessary technical data and costs. In Tab.A.1 costs are denominated in US dollars referred to the base year 2012, i.e. in real dollars. In accordance to the Annual Energy Outlook 2013 [15], we assume an expected inflation rate $i = 1.75\%$ per annum, and a tax rate $T_c = 37\%$. As a reference case, we adopt a nominal WACC rate of 8.5%, in agreement with the assumption of a real weighted average cost of capital of 6.6% adopted in 'Levelized cost of new generation resources in the Annual Energy Outlook 2013' [16].

Inserting a deterministic sequence of costs C_n^x in Eq.(1), assessed for example using a succession of expected values for the fuel costs, generates a deterministic $P^{\mathrm{LC,x}}$. This is how the classic LCOE theory works. Promoting instead such a sequence of costs to well defined stochastic process makes of the LCOE the (time-independent) stochastic variable

$$P^{\mathrm{LC,x}}(\omega), \tag{6}$$

which now has a distribution $p(P^{\mathrm{LC,x}})$, an expected value $\mu^{\mathrm{LC,x}}$ and a variance $(\sigma^{\mathrm{LC,x}})^2$. Hence, we will refer to $P^{\mathrm{LC,x}}$ of Eq.(6) as 'stochastic LCOE', or more simply LCOE.

[3]Notice that the relevant quantity for generation portfolio optimization is not the NPV itself, because doubling the size of a plant would double the NPV, which is not what is sought by portfolio optimization [4].

[4]For example, as shown in [14] and references therein, in the context of deterministic growth theory, this equation can be interpreted as defining the Balanced Growth Equivalent (BGE) of welfare.

In the case of fossil technologies (x = 'co','ga'), denoting by $X_n^x(\omega)$ the stochastic dynamic processes for nominal fuel prices per unit of fuel and by $Z_n(\omega)$ the CO_2 price per ton, we can rewrite Eq.(1) as a linear combination of fuel and carbon contributions:

$$P^{\mathrm{LC,x}}(\omega) = A^x \sum_{n=1}^{M} X_n^x(\omega) F_{0,n} + B^x \sum_{n=1}^{M} Z_n(\omega), F_{0,n} + D^x, \tag{7}$$

where sums run on time n, and D^x is the deterministic component of the LC accounting for all residual terms in Eq.(1), different from fuel and CO_2 costs. Moreover, in Eq.(7)

$$A^x = \frac{H^x}{1000 \sum_{n=1}^{M} (1+i)^{n-n_b} F_{0,n}}, \tag{8}$$

$$B^x = \frac{S^x}{\sum_{n=1}^{M} (1+i)^{n-n_b} F_{0,n}}, \tag{9}$$

where H^x is the fuel heat rate and S_x is the CO_2 intensity (expressed in tCO_2/MWh). Declaring D^x deterministic in Eq.(7) implies that we assumed that other costs have a negligible variance w.r.t. fuel costs volatility. To be noticed that these other costs not only have a negligible variance, but in a gas fired plant about 75% of the generation cost depends on the cost of natural gas, and even if the volatility of coal prices is lower than the volatility of gas prices, in a coal fired plant coal costs are responsible for more than 35% of the generating costs [17]. Most importantly, notice that the second term of $P^{\mathrm{LC,co}}(\omega)$ and $P^{\mathrm{LC,ga}}(\omega)$ (cpr. Eq.(7)) contains the same process $Z_n(\omega)$, making the levelized costs of coal and gas correlated. This correlation will show up in the variance of any portfolio containing both coal and gas. Yet, in the case of nuclear technology, the electricity production doesn't release CO_2 and the main source of uncertainty on $P^{\mathrm{LC,nu}}(\omega)$ is just the duration of the construction period that affects both the initial investment and the fiscal depreciation [18]. In facts, more than 75% of the nuclear LCOE depends on the initial investment and on the time-span of the construction period [17]. On the contrary, other costs (fuel costs, operation and maintenance costs, waste costs and decommissioning costs) have a lower impact on LCOE. For example, the fuel impact on LCOE is about 8% [17]. Uncertainty in the construction time-span affects both the initial investment and the fiscal depreciation and plays, therefore, a crucial role in making the nuclear LCOE a risky variable. $P^{\mathrm{LC,nu}}$ can thus be expressed as follows:

$$P^{\mathrm{LC,nu}}(\omega) = C^{\mathrm{nu}}\left(I_0^{\mathrm{nu}}(\omega) - T_c \sum_{t=1}^{M} dep_n^{\mathrm{nu}}(\omega) F_{0,n}\right) + D^{\mathrm{nu}}, \tag{10}$$

where

$$C^{\mathrm{nu}} = \frac{1}{(1-T_c)Q^{\mathrm{nu}} \sum_{n=1}^{M} (1+i)^{n-n_b} F_{0,n}}. \tag{11}$$

In Eq.(10) D^{nu} is the deterministic component of the LC accounting for all residual terms in Eq.(1). Under this assumption and since the uncertainty about the construction period is not correlated to fossil fuels and carbon prices, a nuclear plant can be seen as a stochastic asset but with zero-covariance with the other fossil fuel assets. In the following, this key modeling feature will be used to hedge the volatility of the LCOE due to fossil fuels and carbon prices volatility.

For a portfolio of technologies, each with weight w^x, the LCOE will be the sum

$$P^{\mathrm{LC,w}}(\omega) = \sum_x w^x P^{\mathrm{LC,x}}(\omega), \tag{12}$$

parametrically dependent on w. Its expectation will be denoted as

$$\mu^{\mathrm{LC,w}} = E[P^{\mathrm{LC,w}}(\omega)] = \sum_x w^x \mu^{\mathrm{LC,x}} \tag{13}$$

where $\mu^{\mathrm{LC,x}} = E[P^{\mathrm{LC,x}}(\omega)]$, and its variance as

$$(\sigma^{\mathrm{LC,w}})^2 = E[(P^{\mathrm{LC,w}}(\omega) - \mu^{\mathrm{LC,w}})^2], \tag{14}$$

the square of the portfolio standard deviation $\sigma^{\mathrm{LC,w}}$[5].

3 LCOE Risk Assessment

In this Section we discuss how to model the uncertainty sources selected in our theory, and what consequences these modeling assumptions have on the stochastic LCOE distribution.

[5] To be noticed that, in analogy to the stochastic extension of BGE introduced in [14], in which the 'Certainty and Balanced Growth Equivalent' (CBGE) is defined, we have a stochastic variable $P^{\mathrm{LC,w}}(\omega)$ which in its expected value $\mu^{\mathrm{LC,w}}$ coincides with the certainty equivalent of the discounted future costs.

3.1 Modelling the Dynamics of Fossil Fuels and CO2 Market Prices

To model fossil fuel and CO2 price processes we follow Lucheroni and Mari [4], modelling them in continuous time, estimating them on market data, then using their values on discrete time sequences. The coal nominal price process is taken as

$$\frac{dX^{\rm co}}{X^{\rm co}} = (\pi^{\rm co} + \pi)dt + \sigma^{\rm co} dW^{\rm co}, \tag{15}$$

where in $\pi^{\rm co} = \ln(1 + \gamma^{\rm co})$ the quantity $\gamma^{\rm co}$ is the real escalation rate of the coal price, chosen as reported in Tab.1, and in $\pi = \ln(1 + i)$ the quantity i is the expected inflation rate, which we choose as $i = 0.0175$ [15]. $\sigma^{\rm co}$ is the volatility of coal prices, which is the only parameter to be estimated on time-series data for this dynamics, and $W^{\rm co}(\omega)$ is a standard Brownian motion.

Coal	Gas
$\gamma^{\rm co} = 0.01$	$\gamma^{\rm ga} = 0.02$
$\pi^{\rm co} = \ln(1.01)$	$\pi^{\rm ga} = \ln(1.02)$

Table 1: Real escalation rates for fossil fuels prices [15].

The gas nominal price dynamics $X^{\rm ga}(\omega)$ is taken as a function

$$X^{\rm ga}(\omega) = e^{(\pi^{\rm ga}+\pi)(t-t_b)} \tilde{X}^{\rm ga}(\omega). \tag{16}$$

of the $\tilde{X}^{\rm ga}(\omega)$ real gas price process. In Eq. (16) the exponential factor accounts for both inflation and real escalation rate of the fuel, where in $\pi^{\rm ga} = \ln(1 + \gamma^{\rm ga})$ the quantity $\gamma^{\rm ga}$ is the real escalation rate of the gas price (see Tab.1). After defining

$$\tilde{\Xi}^{\rm ga}(\omega) = \log \tilde{X}^{\rm ga}(\omega), \tag{17}$$

the dynamics of $\tilde{\Xi}^{\rm ga}(\omega)$ is taken as the jump-diffusion

$$d\tilde{\Xi}^{\rm ga} = (\theta^{\rm ga} - \alpha^{\rm ga}\tilde{\Xi}^{\rm ga})dt + \sigma^{\rm ga} dW^{\rm ga} + JdN, \tag{18}$$

where $\theta^{\rm ga}$ and $\alpha^{\rm ga}$ are mean reversion parameters, $\sigma^{\rm ga}$ is the gas price volatility and $W^{\rm ga}(\omega)$ is a standard Brownian motion. In Eq. (18) $N(\omega)$ is a Poisson process with constant

	Coal	Gas
θ^{ga}		0.0432
α^{ga}		0.0292
λ^{J}		0.2542
σ^{J}		0.1258
σ^{x}	0.0139	0.0737

Table 2: Dynamical parameters.

intensity λ^J, and the jump amplitude J is distributed as a normal random variable with zero mean and standard deviation σ^{J}. The dynamical parameters σ^{co} (for coal prices) and θ^{ga}, α^{ga}, σ^{ga}, λ^J, σ^J (for gas prices) were estimated on US coal and gas market prices since January 1990 until August 2013 and are shown in Tab.2 [4]. Data were taken at a monthly frequency and downloaded from the U.S. Energy Information Administration at site `www.eia.doe.gov/totalenergy`. The dynamics of nominal carbon prices is the $Z(\omega)$ geometric Brownian

$$\frac{dZ}{Z} = \pi dt + \sigma^{\mathrm{ca}} dW^{\mathrm{ca}} \tag{19}$$

where $W^{\mathrm{ca}}(\omega)$ is a standard Brownian motion and σ^{ca} is the carbon volatility. In this case, volatility won't be estimated but it will be taken as a parameter. Z_0 is assumed to be equal to \$ 25 per CO2 ton.

3.2 Modelling Uncertainty in Constructing Nuclear Reactors

Nuclear power is characterized by a large initial investment spanning long construction periods, sometimes due to public acceptance issues. The overnight cost and the duration of the construction period have a very important impact on the LCOE [18]. We describe this uncertainty assuming the construction time to be a stochastic variable K with support k, trying to model its distribution first with a Gaussian distribution and then with a beta-binomial distribution, both with the same mean and the same standard deviation. A Gaussian distribution $N(k; \mu, \sigma^2)$ is a simple and direct model, if one accepts to model construction time as a positive or negative infinite support continuous variable. A beta-binomial distribution, in contrast to the Gaussian distribution, has a finite support of non-negative integers. It is obtained from a binomial distribution $B(k; R, p)$ (where R is the number of trials and p the probability of their success) setting p a random variable itself following a beta distribution $Beta(p; \kappa_\mu, \kappa_\sigma)$ (where $\kappa_\mu > 0$ and $\kappa_\sigma > 0$ are parameters), as

$$BB(k; R, \kappa_\mu, \kappa_\sigma) = \int_0^1 B(k; R, p) Beta(p; \kappa_\mu, \kappa_\sigma)\, dp, \tag{20}$$

which can be written in terms of Gamma functions $\Gamma(k) = \int_0^{+\infty} y^{k-1} e^{-y}\, dy$ as

$$BB(k; R, \kappa_\mu, \kappa_\sigma) = \frac{\Gamma(R+1)}{\Gamma(k+1)\Gamma(R-k+1)} \frac{\Gamma(k+\kappa_\mu)\Gamma(R-k+\kappa_\sigma)}{\Gamma(R+\kappa_\mu+\kappa_\sigma)} \frac{\kappa_\mu+\kappa_\sigma}{\Gamma(\kappa_\mu)\Gamma(\kappa_\sigma)}. \tag{21}$$

For $\kappa_\mu = \kappa_\sigma = 1$ one obtains the discrete uniform distribution from 1 to R. For large κ_μ and κ_σ it approximates the binomial distribution, which in turn can approximate a Gaussian. These properties make it very interesting to model our data on construction times. Moreover, using the method of moments, it can be shown that a beta-binomial distribution can be fit to a sample distribution with first and second sample raw moments $\hat{\nu}_\mu > 0$ and $\hat{\nu}_\sigma > 0$ taking

$$\hat{\kappa}_\mu = \frac{R\hat{\nu}_\mu - \hat{\nu}_\sigma}{R(\hat{\nu}_\sigma/\hat{\nu}_\mu - \hat{\nu}_\mu - 1) + \hat{\nu}_\mu}$$

and

$$\hat{\kappa}_\sigma = \frac{(R-\hat{\nu}_\mu)(R-\hat{\nu}_\sigma/\hat{\nu}_\mu)}{R(\hat{\nu}_\sigma/\hat{\nu}_\mu - \hat{\nu}_\mu - 1) + \hat{\nu}_\mu}$$

as estimates of κ_μ and κ_σ. Thus, we estimated ν_μ and ν_σ on the construction time list of all operating reactors that were built and connected to the grid in the last twenty years (1995-2014) all around the world. These data were collected by 'Nuclear Power Reactors in the World' (2015 Edition) [19], edited the International Atomic Energy Agency (IAEA) and refer to forty reactors built in China (19), India (7), Japan (5), Rep. of Korea (7), Pakistan (1), Russia (1). Appendix B shows the main characteristics of the reactors included in our analysis. The construction period k is expressed in months, as shown in the sixth (last) column of the table. The empirical mean is about 65 months with a standard deviation of about 18 months. Upper panel of Fig.2 shows the counts of the construction times, from

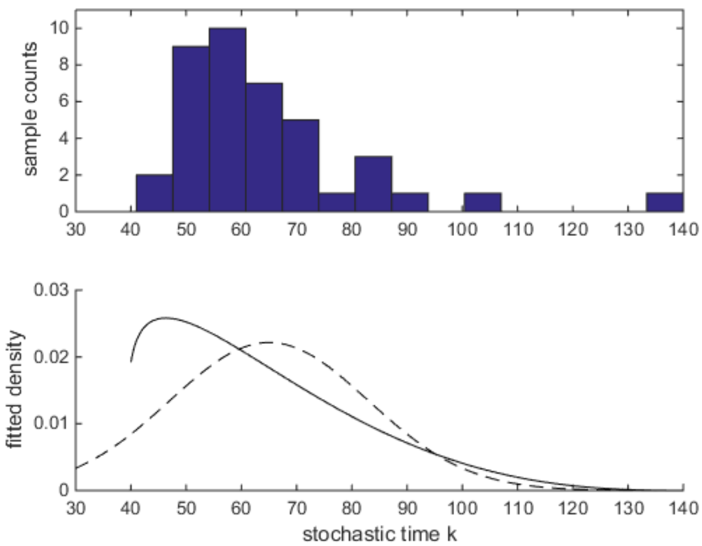

Figure 2: Stochastic construction times. Upper panel: counts; lower panel: fitted Gaussian (broken line) and beta-binomial (solid line) distributions with $\mu = 65$, $\sigma = 18$, $\hat{\kappa}_\mu = 1.20$ and $\hat{\kappa}_\sigma = 3.76$.

which the two beta-binomial parameters can be estimated as $\hat{\kappa}_\mu = 1.20$ and $\hat{\kappa}_\sigma = 3.76$. Lower panel of Fig.2 shows the fitted Gaussian and beta-binomial distributions.

Noticeably, in our case studies we will compute LCOE distributions using US EIA technical data tables [10] (reported in Appendix A), which include a construction period of 6 years for nuclear plants (in Appendix A we indicated this construction time with a 'stoch' label, in order to highlight that we used a full distribution instead of the 6 years figure). Yet, according to Appendix B no new US reactors were connected to the grid in the 1995-2014 period. In order to set up an empirical construction time distribution we thus recurred to international experience, estimating a distribution from Appendix B data. As said, the empirical average of our non-US estimate turns out to be of 65 months (5.4 years), not too distant from US EIA data.

σ^{ca}	fuel	$\mu^{LC,x}$	$\sigma^{LC,x}$	$P^{LC,x}$ skew.	$P^{LC,x}$ kurt.	ρ
0.10	coal	97.4	7.1	0.7	4.1	0.25
	gas	77.2	8.6	0.5	3.5	
0.25	coal	97.4	18.2	5.6	94.2	0.68
	gas	77.2	11.3	2.3	27.1	

Table 3: First four central moments of the $P^{LC,x}$ (LCOE) distribution.

3.3 Fully Stochastic LCOE Model

We assume that $W^{\mathrm{co}}(\omega)$, $W^{\mathrm{ga}}(\omega)$, $W^{\mathrm{ca}}(\omega)$ and $N(\omega)$ processes are mutually independent, and that the construction time stochastic variable K is independent from them. Distributions of single technology and portfolio LCOEs are obtained by Monte Carlo simulations in the following way. Since the coal plus gas sector is independent from the nuclear sector, this sector was simulated first with 10000 Monte Carlo runs, each run consisting of concurrent (but independent) monthly time dynamics of coal, gas and CO2 prices, under two different CO2 scenarios constructed by assuming a CO2 price volatility σ^{ca} equal to either 10% or 25%. Along each time dynamics the sum in Eq.(7) for x='co' and 'ga' was computed, resulting in one sample point for $P^{\mathrm{LC,co}}$ and $P^{\mathrm{LC,ga}}$. In this way marginal sample distributions of $P^{\mathrm{LC,co}}$ and $P^{\mathrm{LC,ga}}$ were collected, dependent on each other because mutually correlated by $Z(\omega)$. Second, 10000 Monte Carlo runs were computed for the nuclear sector, each run differing in the span of construction times, i.e. based on drawing a different k from the estimated distribution (either Gaussian or beta-binomial). The resulting sample distribution of $P^{\mathrm{LC,nu}}$ was collected, independent (then with zero covariance) from any combination of $P^{\mathrm{LC,co}}$ and $P^{\mathrm{LC,ga}}$. Portfolio LCOE distributions can thus be obtained linearly combining the three single technology LCOEs as in Eq.(12), choosing suitable weights w^x. The first four LCOE sample moments for coal and gas obtained in this way, and their sample correlation, are shown in Tab.3 for the two σ^{ca} scenarios. The first four LCOE sample moments for nuclear are shown in Tab.4. Fig.3 shows the four sample marginal LCOE distributions (coal, gas, Gaussian nuclear, beta-binomial nuclear from top to bottom), stacked for easier

distrib.	$\mu^{\text{LC,nu}}$	$\sigma^{\text{LC,nu}}$	$P^{\text{LC,nu}}$ skew.	$P^{\text{LC,nu}}$ kurt.
Gaussian	106.6	5.1	0.2	3.0
beta-binomial	106.6	5.2	1.0	3.6

Table 4: First four central moments of the $P^{\text{LC,nu}}$ (LCOE) distribution.

comparison, for $\sigma^{\text{ca}} = 0.25$. In Fig.3, since the higher is the LCOE (which is nonnegative) the higher is the risk not to cover the costs, on the x axis of each graph the LCOE is shown reversed (i.e. with a minus sign), so that the left tail of the distributions represents a risk of loss. This convention, similar in spirit to the convention of plotting negative returns as l.h.s. tails, will be helpful in the next discussion on risk management. Notice that the distributions of nuclear (Gaussian and beta-binomial) are rather different from each other, and in particular the distribution obtained with the beta-binomial model doesn't in practice have a right tail, but has a long left tail. Notice also that all distributions are strongly asymmetric, have strictly negative support (a LCOE is by definition positive), and in general have very long l.h.s. tails. Long tails mean that low probability scenarios do exist such that break-even can be easily missed. For example, in a scenario where a LCOE worths \$ 240, in order to reach break-even it will be necessary to sell electricity at \$ 240 at minimum, a pretty high figure. Thus, stochastic LCOE theory greatly helps assessing this risk, otherwise neglected in a classic LCOE analysis. In the next Section it will be shown how this risk can be managed.

4 LCOE Risk Management

In this Section we first discuss what we mean by risk in this stochastic LCOE context, then we review the two risk measures that we chose for LCOE optimization, i.e. standard deviation and CVaR deviation, and finally we show the implications of optimizing with respect to these risk measures.

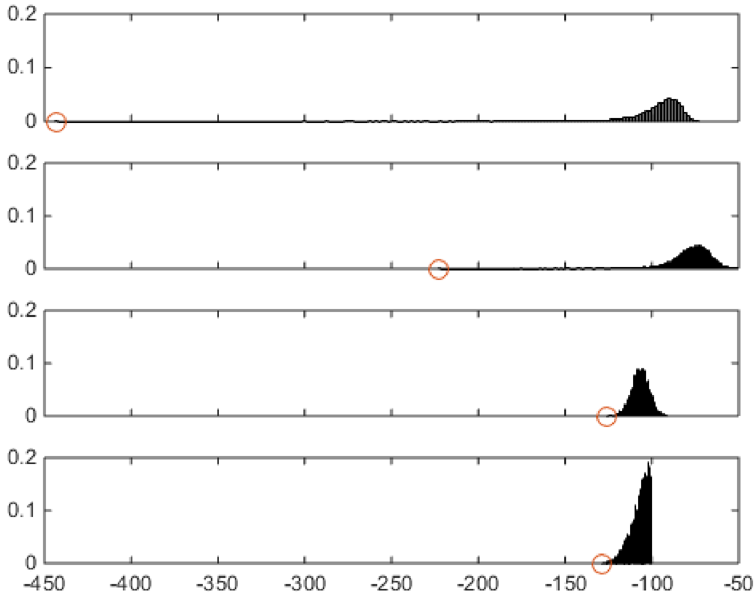

Figure 3: Sample density distributions of single-fuel LCOEs, for $\sigma^{\mathrm{ca}} = 0.25$. Upper: coal; u.middle: gas; l.middle: Gaussian nuclear; lower: beta-binomial nuclear. On the horizontal axis: reversed LCOEs (see text). The circle marks the highest (lowest) LCOE (-LCOE) value.

4.1 What is Risk

Including uncertainty in LCOE calculations promotes LCOE to a stochastic quantity. For an investor which uses deterministic LCOE for capacity planning, information about the LCOE distribution assesses uncertainty. Such an investor can measure this risk with variance, the square of the expected deviation from the mean. A variance averse investor would manage this risk by combining generation assets with weights w^{co}, w^{ga} and w^{nu} in such a way to minimize the risk associated with a given level of LCOE [3]. A more sophisticated investor could yet realize that it is more efficient to be averse to one side of the distribution only, i.e. to LCOEs larger than the mean. In this second case an appropriate risk metrics is still a deviation, but an asymmetric one, like the CVaR Deviation (CVaRD) [4], which is based on CVaR. There are at least two advantages using CVaRD over variance or standard deviation. First, portfolios with a low CVaRD are combinations that minimize the risk of ending up with LCOEs too much larger than their mean, without penalizing as much the favorable possibility of ending up with LCOEs smaller than the mean. Second, CVaRD (like CVaR and unlike standard deviation) is able to properly take into account risk from long tails.

4.2 Deviation Measures

Consider a vector of random variables y with joint probability density $p(y)$, a vector of choice variables w representing portfolio weights, a loss function $f = f(w, y)$ representing portfolio losses (for example, in the LCOE case $f = w'\,y = P^{\mathrm{LC}}$ where y is the vector of single technology LCOEs $y = \{P^{\mathrm{LC,co}}, P^{\mathrm{LC,ga}}, P^{\mathrm{LC,nu}}\}$ and $'$ denotes the transpose), a threshold h for the losses f, and a probability α. As conventional in risk theory notation, losses or other adverse values will be considered as right tail values. The CVaR of the portfolio at confidence level α is defined as the conditional expectation on losses

$$\mathrm{CVaR}_\alpha^w(f) = \frac{1}{1-\alpha} \int_{f(w,y) \geq h^*} f(w,y)\, p(y)\, dy \tag{22}$$

when $h^* = \mathrm{VaR}_\alpha^w(f)$, where

$$\mathrm{VaR}_\alpha^w(f) = \underset{h}{\mathrm{argmin}}\{\int_{f(w,y) \leq h} p(y)\, dy \geq \alpha\} \tag{23}$$

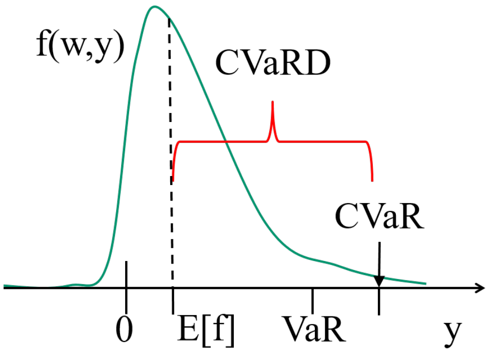

Figure 4: Risk measures associated to a skewed, long tailed generic distribution $f(w,y)$, dependent on given parameters w.

is the portfolio VaR at confidence level α by Uryasev [20] and by Rockafellar and Uryasev [21] (see also [22]). Eq.(23) shows that VaR_α^w is actually an α-quantile, and can be interpreted as the minimum threshold h above which losses are not larger than VaR_α^w in α percent cases of all possible cases. CVaR_α^w can thus be seen as the expectation over the residual $1-\alpha$ cases, the most adverse ones (so that $\mathrm{CVaR}_\alpha^w \geq \mathrm{VaR}_\alpha^w$). In this way, CVaR fully takes into account tail risk, but in an asymmetric way, being defined on the most adverse tail only. Notice that $\mathrm{CVaR}_\alpha^w(f) \geq E[f]$ and if f is equal to a constant c (i.e. it is a deterministic quantity) $\mathrm{CVaR}_\alpha^w(c) = c$. In turn, CVaRD at confidence level α is defined in terms of CVaR as

$$\mathrm{CVaRD}_\alpha^w(f) \equiv \mathrm{CVaR}_\alpha^w(f - E[f]) = \mathrm{CVaR}_\alpha^w(f) - E[f] \tag{24}$$

[23], [9]. The first equality shows that CVaRD is the deviation (and not a risk measure like the CVaR itself) associated to CVaR, like standard deviation σ from $\sigma^2 = E[(f-\mu)^2]$ is associated to the mean μ (which is indeed a risk measure). $\mathrm{CVaRD}_\alpha^w(f)$ is non-negative (like the standard deviation), whereas this is not necessarily true for CVaR (and the mean). If f is equal to a constant c, $\mathrm{CVaRD}_\alpha^w(c) = 0$. Intuitively, the relationship between VaR and CVaRD (or CVaR) is displayed in Fig. 4. Hence, being a deviation, CVaRD has a different field of application than CVaR. The measures useful to manage the risk we have in mind are indeed deviation measures, among which we selected standard deviation (i.e. variance) and CVaRD, with different tail properties.

4.3 Optimal Portfolios Analysis

This selection of two deviation measures can be used to choose an optimal combination of coal and gas assets, nuclear for the moment excluded, in terms of an optimal choice of the portfolio weights w_1, the coal component, and $w_2 = 1 - w_1$, the gas component ($0 \leq w_1 \leq 1$, no 'short selling' allowed), introduced in Eq. (12). We will show how CVaRD improves on usual Markowitz variance.

In [3], a Markowitz portfolio analysis was used to show how to manage the stochastic LCOE risk, for example by computing the variance $(\sigma^{\mathrm{LC,w}})^2$ for a sequence of admissible $\mu^{\mathrm{LC,w}}$, and looking at the generation mix that minimizes the portfolio variance. For a pair of risky assets like coal and gas, $(\sigma^{\mathrm{LC,w}})^2$ vs. $\mu^{\mathrm{LC,w}}$ is a parabola with a minimum at $\mu^{\mathrm{LC}}_{\mathrm{mvp}}$, the minimum variance portfolio, at optimal w^*. In this way, optimization can be introduced in the stochastic LCOE problem, proposing portfolios of assets with minimum deviation from μ^{LC,w^*}. Investment risk is thus controlled by choosing assets in such a way that uncertainty around expected LCOEs is minimal. Adding nuclear as a risk-free asset, the efficient frontier becomes a line [3], [4].

The three asset optimal portfolio selection problem, coal and gas with the nuclear technology as a third asset still with zero-covariance but now risky, shows features which extend those obtained by Mari [3] and by Lucheroni and Mari [4]. In fact, when a zero-covariance but otherwise risky asset is included into the analysis, the efficient frontier is not a line anymore. Using the reversed-axis convention for the ordinate, the next Figures, and in particular Fig.5 and Fig.6, show, on a usual Markowitz plane, all possible generation portfolios that can be obtained in the three asset portfolio selection, respectively for $\sigma^{\mathrm{ca}} = 0.10$ and $\sigma^{\mathrm{ca}} = 0.25$. With this convention, favourable (low LCOE) portfolios appear in the upper part of the graphs, in the usual Markowitz way. The red densely dotted line depicts the portfolio frontier in the two assets (coal and gas) optimization problem, and the black sparsely dotted line shows the portfolio frontier when the nuclear asset is included. Single asset portfolios are clearly visible in the figures as the three tips on the r.h.s. of the dotted region. As expected, the inclusion of a nuclear asset allows one to identify a portfolio

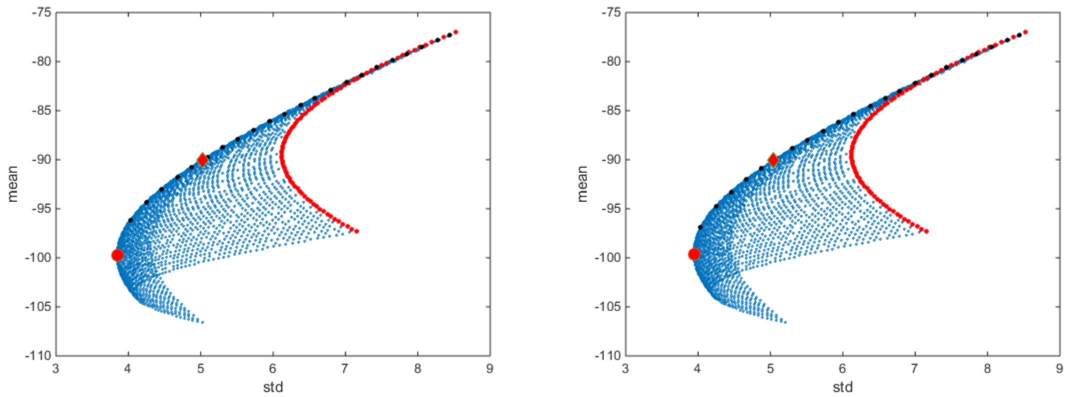

Figure 5: Mean - standard deviation plane for $\sigma^{ca} = 0.10$. L.h.s.: Gaussian case; r.h.s.: beta-binomial case. Red densely dotted line: efficient frontier for the two assets problem, coal and gas. Black sparsely dotted line: efficient frontier with the inclusion of nuclear. The big red dot marks the globally optimum portfolio, the big red diamond marks a portfolio that has the same expected LCOE as the two assets minimum, but a reduced risk because of a nuclear component. Reversed LCOEs convention.

(marked with a red diamond) with the same expected LCOE of the minimum variance portfolio in the two assets selection problem but with a reduced standard deviation risk. From this point of view nuclear technology can be seen as a hedging asset able to reduce the LCOE volatility.

More specifically, in the case of a low volatility CO2 scenario ($\sigma^{ca} = 0.10$, Fig.5), the minimum variance portfolio, when only coal and gas are considered, is characterized by a large coal component, of about 62%, and a residual gas component, of about 38%. The LCOE of such a combination is \$ 90. Inclusion of nuclear greatly modifies this optimal mix. Considering first the Gaussian case (the left panel of Fig.5), at the same level of the generation cost (\$ 90) the nuclear fraction is 29%, the gas component grows to 49% while the coal component reduces to 22%. The same pattern can be observed in the beta-binomial case (the right panel of Fig.5), in which the reduction of the coal component is more pronounced (the nuclear fraction is 33%, the gas component 51% and the coal component reduces to 16%). In the high volatility CO2 scenario ($\sigma^{ca} = 0.25$, Fig.6), the situation is

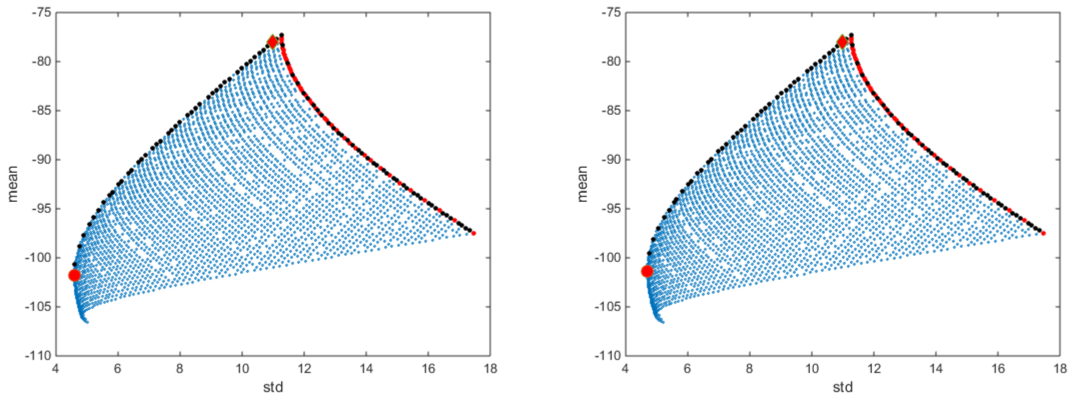

Figure 6: Mean - standard deviation plane for $\sigma^{ca} = 0.25$. L.h.s.: Gaussian case; r.h.s.: beta-binomial case. Red densely dotted line: efficient frontier for the two assets problem, coal and gas. Black sparsely dotted line: efficient frontier with the inclusion of nuclear. The big red dot marks the globally optimum portfolio, the big red diamond marks a portfolio that has the same expected LCOE as the two assets minimum, but a reduced risk because of a nuclear component. Reversed LCOEs convention.

quite different and the optimal portfolio in the two assets problem (coal and gas) is a gas portfolio ($w_1 = 0$). The inclusion of the nuclear does not modify the composition of the optimal portfolio in a significant way both in the Gaussian case and in the beta-binomial case (2.5% is the contribution of nuclear and 97.5% is the gas component). The LCOE of such a combination is about \$ 78 with a higher standard deviation with respect to the low CO2 $\sigma^{ca} = 0.10$ scenario.

In a less obvious way, a CVaRD - expected LCOE plane which includes nuclear displays patterns similar to the standard deviation case. This can be seen in Fig.7 and Fig.8, where all possible three-component portfolios are plotted. The fact that a CVaRD - expected values plane has to show the same features of the standard Markowitz plane is discussed in [24]. As in the standard deviation case, the presence of the nuclear asset reduces portfolio risk. More specifically, in the case of a low volatility CO2 scenario ($\sigma^{ca} = 0.10$, Fig.7), the minimum CVaRD portfolio, when only coal and gas are considered, is an almost equal weights portfolio, namely 53% is the coal component and 47% is the gas component. The

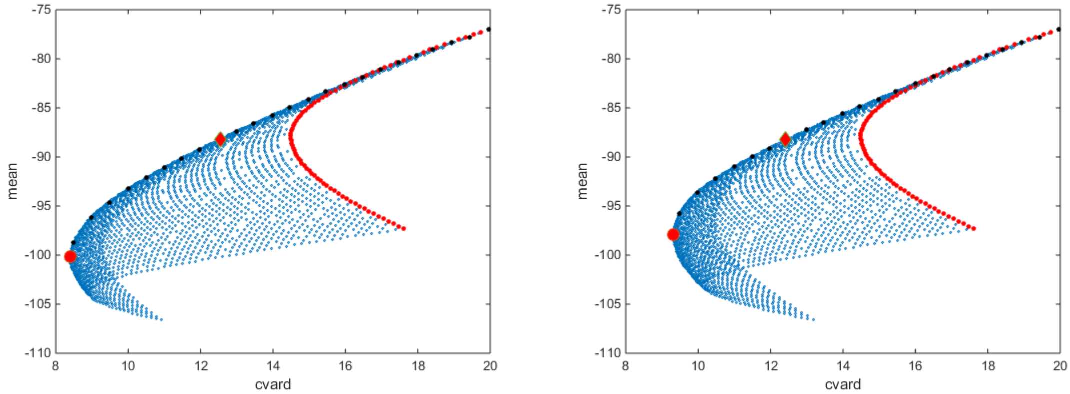

Figure 7: Mean - CVaRD plane, for $\sigma^{ca} = 0.10$. L.h.s.: Gaussian case; r.h.s.: beta-binomial case. Red densely dotted line: efficient frontier for the two assets problem, coal and gas. Black sparsely dotted line: efficient frontier with the inclusion of nuclear. The big red dot marks the globally optimum portfolio, the big red diamond marks a portfolio that has the same expected LCOE as the two assets minimum, but a reduced risk because of a nuclear component. Reversed LCOEs convention.

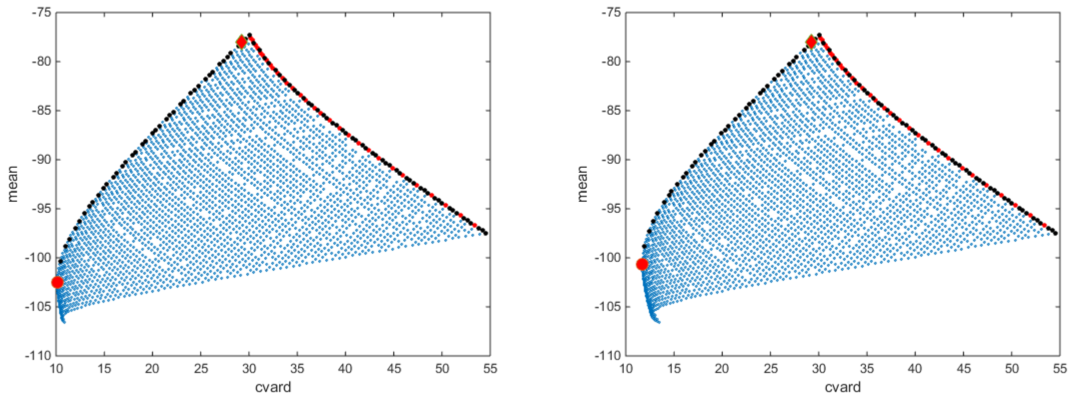

Figure 8: Mean - CVaRD plane for $\sigma^{ca} = 0.25$. L.h.s.: Gaussian case; r.h.s.: beta-binomial case. Red densely dotted line: efficient frontier for the two assets problem, coal and gas. Black sparsely dotted line: efficient frontier with the inclusion of nuclear. The big red dot marks the globally optimum portfolio, the big red diamond marks a portfolio that has the same expected LCOE as the two assets minimum, but a reduced risk because of a nuclear component. Reversed LCOEs convention.

σ^{ca}	distrib.	coal	gas	nuclear
0.10	gaussian	25%	15%	60%
	beta-bin.	27%	15%	58%
0.25	gaussian	0%	17%	83%
	beta-bin.	0%	18%	82%

Table 5: Minimum standard deviation portfolios composition.

LCOE of such a combination is about \$ 88. Due to the large extension of the high LCOE tail in the coal LCOE distribution (see Fig.3), the coal component of the minimum CVarD portfolio is reduced with respect to the minimum variance portfolio. As in the standard deviation case, the inclusion of the nuclear asset modifies in a significant way the optimal mix. In fact, considering first the Gaussian case depicted in the right panel of Fig.7, at the same level of the generation cost (\$ 88), the nuclear fraction is 29%, the gas component growths to 58% while the coal component reduces to 13%. A similar pattern can be observed in the beta-binomial case, shown in the right panel of Fig.7, in which the reduction of the coal component is less pronounced. This is a very important difference with respect to the standard deviation case. The nuclear component is 23% (33% in the standard deviation case) and the coal component 21% (16% in the standard deviation case). The tail effect in the beta-binomial distribution of the nuclear LCOE makes this asset more risky and reduces the hedging effects. The high volatility CO2 scenario ($\sigma^{ca} = 0.25$), depicted in Fig.8, does not show significant differences with respect to the standard deviation case both in the Gaussian case and in the beta-binomial case (2.5% is the contribution of nuclear and 97.5% is the gas component). The LCOE of such combination is about \$ 78 with a higher CVarD value with respect the low CO2 scenario. We notice that in the three assets optimization problem, the global minimum deviation portfolio is always a non trivial combination of coal, gas and nuclear power generation. Tab.5 and Tab.6 show the composition of respectively the minimum standard deviation portfolios and the minimum CVarD portfolios, in both CO2 volatility scenarios.

It is interesting to visually compare the two LCOE distributions selected by the two

σ^{ca}	distrib.	coal	gas	nuclear
0.10	gaussian	22%	15%	63%
	beta-bin.	27%	19%	54%
0.25	gaussian	0%	14%	86%
	beta-bin.	0%	20%	80%

Table 6: Minimum CVarD portfolios composition.

deviation measures in at least one of the studied scenarios, i.e. $\sigma^{ca} = 0.25$, beta-binomial times. Such distributions, shown in Fig.9, were assembled using data from last rows of Tab.5 and Tab.6. In this Figure, the two distributions are shown as a darker (blue) one and a lighter (yellow) one. The darker distribution is the distribution with global minimum standard deviation. The lighter distribution is the distribution with global minimum CVaRD. In both cases, the range of possible LCOEs is greatly reduced w.r.t. the range that can be obtained from combinations of long-tailed fossil technologies only (the square and the dot in the Figure mark the highest possible LCOEs of the two distributions), but in comparison CVaRD (lighter color distribution) selects a portfolio which is clearly more left-side-risk (large LCOEs) averse than the portfolio selected by standard deviation. This happens in all scenarios.

Finally, it is worthwhile to notice that with portfolio compositions available as in Tab.5 and Tab.6, it is possible to quantitatively assess how much emissions can be reduced, making use of the CO2 intensity coefficients reported in Appendix A. We leave this more quantitative analysis for further work, just pointing out that such an assessment is possible with the stochastic LCOE theory only.

4.4 CO2 emissions assessment

The stochastic LCOE theory is also an important tool of analysis to jointly investigate diversification effects and CO2 emissions reduction due to electricity generation portfolio selection. The combined effect of fossil fuels prices volatility and CO2 price volatility controls CO2 emissions, to an extent that can be quantified.

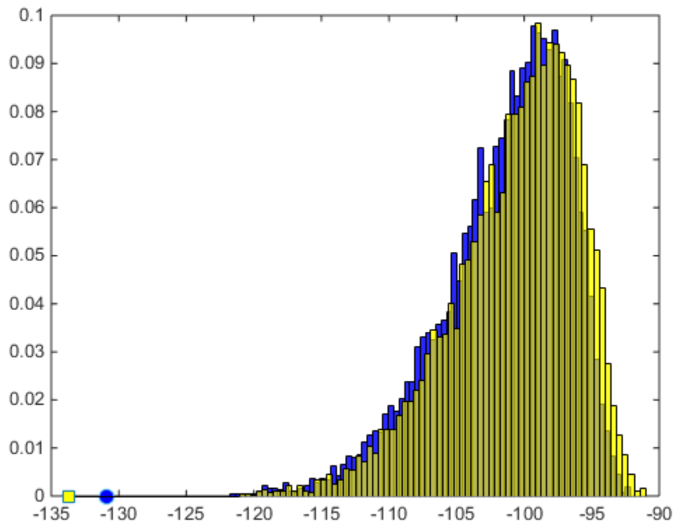

Figure 9: Comparison of distributions selected by global minimum standard deviation and global minimum CVaRD. The (blue) darker distribution is the distribution with global minimum standard deviation. The (yellow) lighter distribution is the distribution with global minimum CVaRD. The (blue) dot marks minimum standard deviation LCOE, the (yellow) square marks minimum CVaRD. Reversed LCOEs convention.

Let us recall that the CO2 emissions rate of a power generation portfolio can be computed as a linear combination of single technology emissions rate using as weights the fraction of energy generated by each single technology in the portfolio. Denoting by $E^{\mathrm{C02},x}$ the CO2 emissions rate due to technology x measured in tCO2/MWh, the portfolio emissions rate, $E^{\mathrm{C02},w}$, is given by

$$E^{\mathrm{C02},w} = \sum_x w^x E^{\mathrm{C02},x}. \tag{25}$$

Fifth row of Tab.7 shows emissions rates for optimal standard deviation portfolios. Emissions are computed using an emissions rate of 0.832 tCO2/MWh for coal fired plants and 0.375 tCO2/MWh for gas fired plants [10]. The inclusion of the nuclear asset into the analysis reduces both the risk and the CO2 emissions rate: the abatement of CO2 emissions (last row of Tab.7) is about 44% in the Gaussian case and about 51% in the beta-binomial case. Last column of Tab.7 shows the composition of the minimum emissions portfolio (mep). It has been determined as the two assets generation portfolio composed by gas and nuclear power with LCOE equal to \$ 90. Due to the absence of the coal component, this optimal CO2 portfolio shows a greater rate of CO2 reduction (68%). The volatility of market gas prices is responsible of the inclusion of the coal in the financial optimal generation mixes and for this reason such optimal portfolios does not coincide with the minimum emissions portfolio. Similar patterns can be observed when CVarD is used as a risk measure (Tab.8). The inclusion of the nuclear asset into the analysis reduces both the risk and the CO2 emissions rate, even if the CO2 abatement is more pronounced in the Gaussian case with respect to the beta-binomial case. The tail of the nuclear LCOE reduces not only the hedging effect but also the CO2 abatement effect. The volatility of CO2 prices has a strong effect on generation portfolios. In Tab.9 and Tab.10 the components of the minimum deviation portfolios are shown together with their related emission rates in both scenarios. Specifically, in the high volatility scenario ($\sigma^{ca} = 0.25$), the coal component is zeroed by the minimum deviation portfolios. Thus, in the presence of CO2 volatility, rational choice pushes toward a larger share of low carbon fuels. Moreover, when nuclear is part of an energy portfolio, this beneficial effect of CO2 volatility is further enhanced.

LCOE=90	two assets	gaussian	beta-bin.	mep
w^{co}	62%	22%	16%	0%
w^{ga}	38%	49%	51%	56%
w^{nu}	0%	29%	33%	44%
tCO2/MWh	0.66	0.37	0.32	0.21
CO2 abat.		-44%	-51%	-68%

Table 7: Standard deviation optimal portfolios ($\sigma^{ca} = 0.10$) composition for LCOE=90, CO2 emissions rates and CO2 abatements. mep stands for minimum emissions portfolio.

LCOE=88	two assets	gaussian	beta-bin.	mep
w^{co}	53%	13%	21%	0%
w^{ga}	47%	58%	56%	63%
w^{nu}	0%	29%	23%	37%
tCO2/MWh	0.62	0.33	0.38	0.24
CO2 abat.		-47%	-38%	-62%

Table 8: CVarD optimal portfolios ($\sigma^{ca} = 0.10$) composition for LCOE=88, CO2 emissions rates and CO2 abatements. mep stands for minimum emissions portfolio.

Better than prices, CO2 volatility forces producers to reduce the coal component of their generation portfolios and, as a consequence, to reduce CO2 emissions. From this point of view, the existence of CO2 volatility can be beneficial to the environment.

5 Concluding Remarks

We have shown how CO2 price volatility, which is peculiar of market oriented carbon pricing mechanisms, rather intriguingly allows to reduce CO2 emissions. The effect of CO2 price volatility on investment decisions of rational electricity producers consists of inducing them to include nuclear technology, a CO2 free fuel, in their coal and gas generation portfolios of baseload electricity production in order to hedge investment risk. This effect can be quan-

	gaussian		beta-bin.	
	$\sigma^{ca} = 0.10$	$\sigma^{ca} = 0.25$	$\sigma^{ca} = 0.10$	$\sigma^{ca} = 0.25$
w^{co}	25%	0%	27%	0%
w^{ga}	15%	17%	15%	18%
w^{nu}	60%	83%	58%	82%
tCO2/MWh	0.26	0.06	0.28	0.07

Table 9: CO2 emissions rates of minimum standard deviation portfolios for $\sigma^{ca} = 0.10$ and $\sigma^{ca} = 0.25$.

	gaussian		beta-bin.	
	$\sigma^{ca} = 0.10$	$\sigma^{ca} = 0.25$	$\sigma^{ca} = 0.10$	$\sigma^{ca} = 0.25$
w^{co}	22%	0%	27%	0%
w^{ga}	15%	14%	19%	20%
w^{nu}	63%	86%	54%	80%
tCO2/MWh	0.24	0.05	0.30	0.08

Table 10: CO2 emissions rates of minimum CVarD portfolios for $\sigma^{ca} = 0.10$ and $\sigma^{ca} = 0.25$.

tified using the fully stochastic LCOE theory, by providing portfolios of power generation assets optimal under deviation measures, like for example standard deviation and CVaRD. Depending on the kind of risk to be hedged, either symmetric dispersion risk around LCOE or tail dispersion risk, and depending on the expected CO2 volatility scenario, a rational investor will select different mixes of power generation technologies. In a low volatility scenario (like $\sigma^{ca} = 0.10$), minimum dispersion portfolios will be very much diversified, containing a significant fraction of all three technologies. Such a diversification is reduced as expected CO2 price volatility increases (for example to $\sigma^{ca} = 0.25$). In the high volatility scenario coal technology is abandoned and minimum dispersion portfolios will be composed of two technologies only, namely gas and nuclear, with a large nuclear component.

Moreover, the proposed theory can be used to infer the possibility of a role of CO2 prices volatility on emissions control. As shown in this paper, it allows to assess in a quantitative way emissions reduction when risk averse investors adopt the stochastic LCOE approach. This theory can be hence used both from an investor's point of view - hedging perspective cost fluctuations and extreme cost events when expanding capacity, and from a policy maker's point of view - assessing system wide costs (including environmental costs) and risks, and guiding investors by means of tuned up CO2 price mechanisms.

One could think of repeating this stochastic LCOE analysis by substituting nuclear technology with some renewable energy technology as the carbon free asset. The inclusion of renewable energy to hedge CO2 and fossil fuels prices volatility is not straightforward, especially for intermittent sources like wind or solar. In this case, two main extensions of the theory would be necessary. The first one consists of providing a suitable definition of generation costs for intermittent renewable technologies, because intermittency originates extra costs which must be properly included in the LCOE calculation. One possibility for assessing these costs and their risk could be to consider an intermittent source as an otherwise renewable source but coupled to a programmable technology like a gas plant. The second extension regards the correct inclusion of risk from random annual production itself. Once both extensions are explored and understood, the fully stochastic LCOE theory will allow us to include renewable sources into energy portfolio optimization. We leave these extensions to future investigations.

References

[1] Pfenninger S, Keirstead J. Renewables, nuclear, or fossil fuels? Scenarios from Great Britain's power system considering costs, emissions and energy security. Applied Energy 2015; 152:83-93.

[2] Tolis AI, Rentizelas AA. An impact assessment of electricity and emission allowances pricing in optimised expansion planning of power sector portfolios. Applied Energy 2011; 88:3791-806.

[3] Mari C. Hedging electricity price volatility using nuclear power. Applied Energy 2014; 113:615-21.

[4] Lucheroni C, Mari C. Risk shaping of optimal electricity portfolios in the stochastic LCOE theory. Submitted to Energy Economics, October 2015. Preprint available on ResearchGate (Lucheroni) DOI: 10.13140/RG.2.1.3404.8729.

[5] Hong S, Bradshaw C, Brook BW. Nuclear power can reduce emissions and maintain a strong economy: Rating Australia's optimal future electricity-generation mix by technologies and policies. Applied Energy 2014; 136:712-25.

[6] Chen Q, Tang Z, Lei Y, Sun Y, Jiang M. Feasibility analysis of nuclear-coal hybrid energy systems from the perspective of low-carbon development. Applied Energy 2015; 158:619-30.

[7] González-Pedraz C, Moreno M, Peña JI. Tail risk in energy portfolios. Energy Economics 2014; 46:422-34.

[8] Sarykalin S, Serraino G, Uryasev S. Value-at-risk vs. conditional value-at-risk in risk management and optimization. Informs 2008 Proceedings.

[9] Rockafellar RT, Uryasev S. The fundamental risk quadrangle in risk management, optimization and statistical estimation. Surveys in Operations Research and Management Science 2013; 18:33-53.

[10] EIA, 2013. Updated capital cost estimates for utility scale electricity generating plants. U.S. Energy Information Administration, Department of Energy.

[11] Markowitz H. Porfolio selection. Journal of Finance 1952; 77:77-91.

[12] MIT, 2003. The future of nuclear power. Cambridge, United States.

[13] Ross SA, Westerfield RW, Jaffe J. Corporate Finance. McGraw-Hill 2010.

[14] Anthoff D, Tol RSJ. The impact of climate change on the balanced growth equivalent: An application of *FUND*. Environ Resource Econ 2009; 43:351-67.

[15] EIA, 2013. Annual energy outlook 2013. U.S. Energy Information Administration, Department of Energy.

[16] EIA, 2013. Levelized cost of new generation resources in the annual energy outlook 2013. U.S. Energy Information Administration, Department of Energy.

[17] Mari C. The costs of generating electricity and the competitiveness of nuclear power. Progress in Nuclear Energy 2014; 73:15361.

[18] Kessides IN. Nuclear power: Undestanding the economic risks and uncertainties. Energy Policy 2010; 38:3849-64.

[19] IAEA, 2015. Nuclear Power Reactors in the World. International Atomic Energy Agency.

[20] Uryasev S. Conditional value-at-risk: Optimization algorithms and applications. Financial Engineering News 2000; 14.

[21] Rockafellar RT, Uryasev S. Optimization ofconditional value-at-risk. The Journal of Risk 2000; 2:21-41.

[22] Krokhml P, Palmquist J, Uryasev S. Portfolio optimization with conditional value-at-risk: Objective and constraints. The Journal of Risk 2002; 4 (2):43-68.

[23] Rockafellar RT, Uryasev S, Zabarankin M. Generalized deviations in risk analysis. University of Florida Dept. of Industrial and Systems Engineering WP No. 2004-4. Available at SSRN: http://ssrn.com/abstract=587441.

[24] Rockafellar RT, Uryasev S, Zabarankin M. Master funds in portfolio analysis with general deviation measures. Journal of Banking & Finance 2006; 30(2):743-78.

[25] MIT, 2009. Update of the MIT 2003 - The future of nuclear power. Cambridge, United States.

[26] Du Y, Parsons JE. Update on the cost of nuclear power. MIT Working Paper 2009.

A Technical assumptions

	Units	Nuclear	Coal	Gas
Technology symbol		nu	co	ga
Capacity factor		90%	85%	87%
Heat rate	Btu/kWh	10452	8800	7050
Overnight cost	$/kW	5530	2934	917
Fixed O&M costs	$/kW/year	93.28	31.18	13.17
Variable O&M costs	mills/kWh	2.14	4.47	3.60
Fuel costs	$/mmBtu	0.74	stoch.	stoch.
CO_2 intensity	Kg-C/mmBtu	0	25.8	14.5
Waste fee	$/kWh	0.001	–	–
Decommissioning cost	$ million	750	–	–
O&M real escalation rate		1.0%	1.0%	1.0%
Fuel real escalation rate		0.5%	1.0%	2.0%
Construction period	# of years	stoch.	4	3
Operations start		2018	2018	2018
Plant life	# of years	40	40	40
Depreciation scheme		MACRS,15	MACRS,20	MACRS,15

Table A.1: Technical assumptions. All dollar amounts are in year 2012 dollars. Overnight costs are assumed to be uniformly distributed on the construction period. O&M stands for operation and maintenance. Mill stands for 1/1000 of a dollar. mmBTU stands for one million BTUs. Depreciation is developed according to the MACRS (Modified Accelerated Cost Recovery System) scheme. 'Stoch.' stands for stochastic.

Data shown in Tab.A.1 are collected from the 'Annual Energy Outlook 2013' [15] as reported in 'Updated Capital Cost Estimates for Utility Scale Electricity Generating Plants' [10] provided by the U.S. Energy Information Administration, integrated with data from 'The Future of Nuclear Power' (2003) by the Massachusetts Institute of Technology [12] and its last update 'Update of the MIT 2003 - Future of Nuclear Power' [25], [26].

Asset depreciation, dep_n^x, is technology dependent and it is computed using the MACRS system (Modified Accelerated Cost Recovery System), displayed in the table below.

	MACRS,15	MACRS,20
Year 1	5.00%	3.750%
Year 2	9.50%	7.219%
Year 3	8.55%	6.677%
Year 4	7.70%	6.177%
Year 5	6.93%	5.713%
Year 6	6.23%	5.285%
Year 7	5.90%	4.888%
Year 8	5.90%	4.522%
Year 9	5.91%	4.462%
Year 10	5.90%	4.461%
Year 11	5.91%	4.462%
Year 12	5.90%	4.461%
Year 13	5.91%	4.462%
Year 14	5.90%	4.461%
Year 15	5.91%	4.462%
Year 16	2.95%	4.461%
Year 17		4.462%
Year 18		4.461%
Year 19		4.462%
Year 20		4.461%
Year 21		2.231%

Table A.2: Depreciation Schedule.

B Nuclear Reactors Data

The table below displays the list of nuclear reactors constructed during the last twenty years (1995-2014). The duration of the construction period, reported in the last column, is expressed in months (m).

Country	Reactor	Type	Constr. start	Grid conn.	Time (m)
CHINA	FANGJIASHAN-1	PWR	2008-12	2014-11	72
	FUQING-1	PWR	2008-11	2014-08	70
	HONGYANHE-1	PWR	2007-08	2013-02	67
	HONGYANHE-2	PWR	2008-03	2013-11	69
	LING AO-1	PWR	1997-05	2002-02	58
	LING AO-2	PWR	1997-11	2002-09	59
	LING AO-3	PWR	2005-12	2010-07	56
	LING AO-4	PWR	2006-06	2011-05	60
	NINGDE-1	PWR	2008-02	2012-12	59
	NINGDE-2	PWR	2008-11	2014-01	63
	QINSHAN 2-1	PWR	1996-06	2002-02	69
	QINSHAN 2-2	PWR	1997-04	2004-03	84
	QINSHAN 2-3	PWR	2006-04	2010-08	53
	QINSHAN 2-4	PWR	2007-01	2011-11	59
	QINSHAN 3-1	PHWR	1998-06	2002-11	54
	QINSHAN 3-2	PHWR	1998-09	2003-06	58
	TIANWAN-1	PWR	1999-10	2006-05	80
	TIANWAN-2	PWR	2000-09	2007-05	81
	YANGJIANG-1	PWR	2008-12	2013-12	61
INDIA	KAIGA-3	PHWR	2002-03	2007-04	62
	KAIGA-4	PHWR	2002-05	2011-01	105
	KUDANKULAM-1	PWR	2002-03	2013-10	140

Country	Reactor	Type	Constr. start	Grid conn.	Time (m)
INDIA	RAJASTHAN-5	PHWR	2002-09	2009-12	88
	RAJASTHAN-6	PHWR	2003-01	2010-03	87
	TARAPUR-3	PHWR	2000-05	2006-06	74
	TARAPUR-4	PHWR	2000-03	2005-06	64
JAPAN	HAMAOKA-5	BWR	2000-07	2004-04	46
	HIGASHI DORI-1	BWR	2000-11	2005-03	53
	ONAGAWA-3	BWR	1998-01	2001-05	41
	SHIKA-2	BWR	2001-08	2005-07	48
	TOMARI-3	PWR	2004-11	2009-03	53
KOREA, REP. OF	HANBIT-5	PWR	1997-06	2001-12	55
	HANBIT-6	PWR	1997-11	2002-09	59
	HANUL-5	PWR	1999-10	2003-12	51
	HANUL-6	PWR	2000-09	2005-01	53
	SHIN KORI-1	PWR	2006-06	2010-08	51
	SHIN KORI-2	PWR	2007-06	2012-01	56
	SHIN WOLSONG-1	PWR	2007-11	2012-01	51
PAKISTAN	CHASNUPP-2	PWR	2005-12	2011-03	64
RUSSIA	ROSTOV-3	PWR	2009-09	2014-12	64