Minimizing Cost Uncertainty with a New Methodology for Use In Policy Making: China's Electricity Pathways

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***Abstract*— Planning the long-term expansion of a power sector requires anticipating future technology, fuel costs, and new carbon policies. Many state-of-the-art models rely on exogenous data for cost and performance projections where the inherent uncertainty is either ignored or addressed only with sensitivity analysis and scenarios. For the few models accounting for uncertainty, the transition from the research field to policy making has not occurred because of important practical barriers in the latter field: higher reliance on time-tested models, impossibility to constantly adopt new models, run-time issues. To streamline this process, we present a new modular two-step methodology, based on mean-variance optimization, to help policy makers adjust for risks on costs their findings from current cost-minimizing tools, while sparing them the hurdles of adopting a new model. To illustrate this, we refine the SWITCH-China least-cost electricity pathway by minimizing its cost uncertainty.**

***Index Terms*— China, Planning, Optimization, Power Sector, Uncertainty**

I. Introduction *(Heading 1)*

The ability of the world to meet its growing electricity needs while reducing carbon emissions will depend on countries' capacity to forecast and plan optimal actions to take now and in the next decades. Given the large numbers of parameters at stake, multiple modeling tools have been developed to help governments, policy makers, utilities, and investors plan and optimize long-term expansion of the power sector. Traditional linear programming (LP) cost-minimization tools give insight into the energy sources to be considered. However, among a set of possible expansion trajectories for the future electricity mix with similar yet not identical costs, LP models choose least-cost options without accounting for the probability that the projected costs might not match actual future costs. Because of the inherent uncertainty on exogenous cost projections, the stability of the costs, i.e. the affordability of the mix, is not ensured by such cost-minimizing tools. Yet, policy makers seek to include in their decision-making the likelihood that future costs would remain close to projected costs should the scenario be implemented. In this case, optimizing an electricity portfolio is a trade-off between the minimization of expected cost: E[c], and the minimization of uncertainty, or "risk', on costs: σ[c]. The best LP tools currently used by policy makers are, in fact, complex, joint optimization efforts, where often the variables of interest (such as reliability, cost effective emissions minimization) operate at cross purposes. It is critical for energy planners to not only receive advice from experts, but to be able to understand the basis and implications of those recommendations. Creating a tool that can be used to simultaneously minimize *costs* and *risk on costs* would surely prove to be a valuable asset for long-term planning of the energy mix. However, given the myriad of existing models presenting various – sometimes very similar – approaches for planning the future electricity mix, and the adaptation time that is required to transition the new modeling tool from a research-based usage to a policy-making usage, decision makers tend to favor time-tested tools over newer, more efficient models. Unfortunately, the majority of those time-tested tools do not account for risks. In this paper, we propose a new approach to account for risk aversion while allowing decision makers to use cost minimization tools they are familiar with.

A common way to address uncertainty in energy planning modeling tools is the use of scenarios [1], such as current versions of the SWITCH model [2] [3] [4], or sensitivity analysis, such as in the HOMER model [5]. The amplitude of these approaches is limited as it relies on human imagination, often qualitative rather than quantitative (for e.g., "high gas price" and "low gas price" scenarios). There exist two methods to account for risks that combine well with 'static programming' tools of used by policy makers: repeated random sampling (e.g. Monte Carlo simulations) and portfolio management. The former is based on simulations while the latter is based on optimization. The main caveat of random sampling is the impossibility to ensure that all possible, rare but high-consequence events have been simulated. This is related to the problem of induction illustrated by the inference: *Every swan that I have ever seen is white, therefore there is no black swan* [6]. Another related issue is the large number of outcomes from the simulations leaving policy makers with a range of options and possible futures almost as broad as the initial set of options.

Mean-variance optimization poses some reliability challenges too, as it often assumes no uncertainty on the uncertainty: the standard deviation is assumed to be known. While this can be problematic in branches of finance subject to a selection bias [7], centralized long-term expansion planning of a national electricity mix is usually less subject to this bias. Past data that energy planners rely on to create cost projections is comprehensive, based on existing data such as historical market prices for fuel and past construction and operation costs for energy systems. While the average values of this past data cannot be considered as an accurate prediction of future costs, the typical scope embraced is usually old and large enough to represent an accurate landscape of the range of future possibilities. For these reasons, we choose mean-variance optimization over random sampling in the present study.

Policy makers could comprehensively plan expansion of the electricity mix through two successive steps. The first one, already performed by most energy planners, involves the identification of least-cost installed capacity or generation levels for various power sources or technologies, via a thorough linear cost-minimization with an existing modeling tool. The second step, proposed in this study, consists in allowing slight deviations around each energy source generation levels previously identified. By setting a sufficiently narrow limit for allowed deviations – i.e. a 'reliability net' –, this second step refines results of least-cost electricity mixes obtained from complex cost-minimizing modeling tools by confronting them against a simpler risk-minimization model, while preserving the grid reliability ensured by the LP tool.

China's power system is an ideal laboratory as the country presents a centrally-planned power sector facilitating the optimization of the mix at the national scale. Moreover, the extent of China's future demand is such that adapting the electricity supply will require novel, unconventional technologies, for which taking risk on costs into account is crucial.

The second section of this paper presents the methodology on risk calculation and the quadratic program formulated to perform the mean-variance analysis. The third section is a case study of the two-step optimization process applied to the Chinese power sector. In this last section, we use the SWITCH model as a proxy for advanced linear programming cost-minimizing models used by policy makers.

From its original purpose in the field of finance [8], modern portfolio theory (MPT) has been extended to other contexts. The application of MPT to energy portfolio management can be traced back from 1976 [9], however it has only significantly expanded these last years [10] [11] [12] [13], together because of increasing environmental awareness and subsequent regulations, novel technologies resulting in uncertain risk and return, and deregulation of electricity markets. However, loose assumptions lead to important discrepancies between Pareto optima modeled with different beliefs, illustrated for example by comparing these two analyses performed on the Chinese power sector [14] [15]. The novelty of the current study lies in several areas. First, we propose a high-fidelity method as we constrain the risk-minimization analysis in order to preserve the grid reliability ensured by the high-resolution linear-program model. Second, we use several hundred thousand historical hourly capacity factors for central PV and wind turbines across China in order to assess the magnitude of the uncertainty resulting from generation intermittency. Third, as our study focuses on improving the quality of energy planning from a policy making perspective, we create an original two-step process ensuring easy adoption of the tool by policy makers.

II. METHODOLOGY

A. *Risk factors*

Mean-variance portfolio analysis uses the variance of return or cost projections as a metric to quantify the impact of uncertainty on the objective. Here, we assume that cost probabilities are normally distributed. Therefore, cost projections found in the literature correspond to the mean of the probability distribution. Variances are either obtained from the literature or calculated based on multiple data.

The following factors of uncertainty are taken into account: overnight costs ($\sigma_{overnight}$); uncertainty resulting from fuel price volatility and future carbon tax (σ_{fuel}); fixed operation and maintenance costs, including potential future safety regulations for nuclear power ($\sigma_{O\&M}$); intermittency of wind and solar power output ($\sigma_{intermittent}$)

While the risk on costs resulting from short-term intermittency of variable renewable energies have not, to the best of our knowledge, been covered in the existing literature, here we present a simple methodology to calculate the standard deviations resulting from the variability renewable energies. For a given region, we use capacity factors for solar PV and wind turbines from historical data. In order to translate these into risk on costs, we make the assumption that intermittency from technology t must be backed by peaker plants, typically gas combustion turbines. :

The standard deviations for the cost components (overnight costs, fuel costs, fixed O&M costs, intermittency costs) are aggregated following the Bienaymé formula.

Levelized Cost of Electricity (LCOE) per energy technology per year is calculated using cost projections, based on the EIA formula [16]. A standard deviation of LCOE per technology per year, expressed in $/MWh, is calculated. These values are the components of the Hessian matrix.

B. *Quadratic-programming model description*

The program formulated in this study is a quadratic program (QP) with linear constraints. Since it is designed as a module to be used after a thorough cost-minimization, it must not be redundant to the first step. The LP used in the first step is assumed to optimize transmission lines, storage capacity, and hourly dispatch of the electricity grid in order to ensure reliability of the grid; therefore these components are not taken into account in the QP. The 'reliability net' within which the QP is allowed to minimize risk is outlined by boundaries of ± 15% around the generation levels of each energy technology in the least-cost portfolio calculated by the LP. We assume that a change of 15% in new capacity does not lead to major siting issues, eliminating the need to account for additional infrastructure/transmission costs in the QP than planned in the LP.

Our objective is to minimize the system's total variance on cost. The subscript -S in the constraints designates the outputs of the cost-minimization model, used as inputs in the risk-minimization model.

$$\min \frac{1}{2} x^T Q x \quad (2)$$

With:

$$x = (x_i) \in \mathbb{R}^{n\times 1} \quad (3)$$

$$Q = (\sigma_i \times \sigma_j \times \rho_{ij}) \in \mathbb{R}^{n\times n} \quad (4)$$

Subject to:

$$\forall i, x_i \geq 0 \quad (5)$$

Reliability net: $\forall i, 0.85 x_{i-S} \leq x_i \leq 1.15 x_{i-S}$ (6)

Carbon emissions are capped at LP level: $\sum_{i=1}^{n} e_i \times x_i \leq \sum_{i=1}^{n} e_i \times x_{i-S}$ (7)

Preserving intermittency back-up (gas plants here):

$$\frac{x_{wind}+x_{solar}}{x_{gas}} \leq \frac{x_{wind-S}+x_{solar-S}}{x_{gas-S}} \quad (8)$$

Annual demand: $\sum_{i=1}^{n} x_i = \sum_{i=1}^{n} x_{i-S}$ (9)

Total cost: $\sum_{i=1}^{n} c_i \times x_i = TC$ (10)

TABLE 1 NOMENCLATURE

Symbol	Definition
n	Number of technologies
x_i	Power generation from technology i (MWh/y)
x	Vector of x_i
σ_i	Standard deviation of LCOE for technology i ($/MWh)
ρ_{ij}	Correlation coefficient between technologies i and j
c_i	LCOE of technology i ($/MWh)
TC	Total power production cost ($/y)
Q	Covariance (or Hessian) matrix: Q = 2*[$\rho ij \times \sigma i \times \sigma_j$]
A	Inequality constraint matrix (left-hand side)
b	Inequality constraint matrix (right-hand side)
Aeq	Equality constraint matrix (left-hand side)
Beq	Equality constraint matrix (right-hand side)
e_i	Intensity of CO_2 emissions from technology i (tCO_2/MWh)

III. CASE-STUDY: CHINA'S ELECTRICITY MIX EXPANSION PLANNING

We apply the two-step methodology to the example of China's power sector.

A. *SWITCH-China cost minimization*

SWITCH is a linear programming tool used to simulate least-cost generation, transmission and storage capacity expansion pathways of the power sector under various policy and cost scenarios. Several versions of SWITCH exist including one for China [2]. Here, the SWITCH model is used as a proxy for cost-minimization models used by policy makers. It combines high spatial and temporal resolutions, and optimizes long-term capacity expansion and hourly generation dispatch simultaneously, ensuring a reliable operation of the grid on both small and large time scales. Investment decisions in SWITCH are divided into four ten-year long periods: 2015-2024, 2025-2034, 2035-2044 and 2045-2054.

For this study, besides SWITCH's usual constraints such as ensuring hourly matching of load and supply, we use a Business-As-Usual scenario with a carbon cap from 2030 on, as announced by President Xi Jinping in November 2014 [17]. We use SWITCH to obtain the corresponding least-cost expansion pathway for the power sector over the 2015-2050 period.

SWITCH accounts for both existing (before 2015) and new plants, adding up to a total of 9 technologies. For practical reasons, the risk minimization is only performed over technologies whose total installed capacity is increased over time in the SWITCH simulation. These technologies are coal steam turbine, gas combustion turbine, wind turbine, solar PV, nuclear PWR and, from 2035 on, coal steam turbine with carbon capture and storage (CCS). The share of 'new capacity', added by SWITCH, is shown on Figure 1 for each of the six technologies.

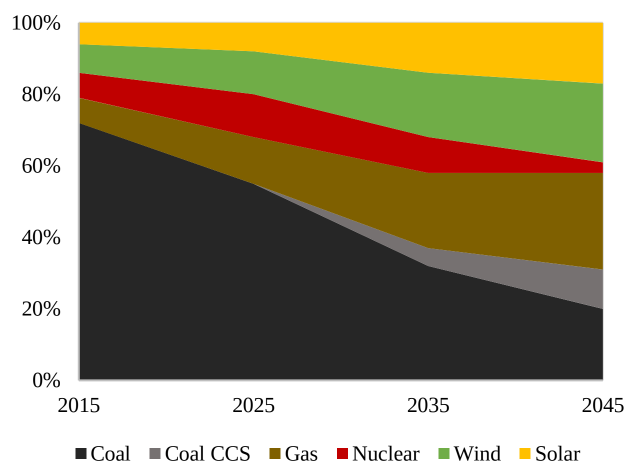

Figure 1 Share of average electricity generated over time from the six technologies in the least-cost energy mix trajectory (SWITCH optimization)

Following this optimization, the resulting annual electricity generation per technology in the least-cost portfolio is used as input in the QP.

Values for expected costs come from [2]. Values for standard deviations on cost components of generation technologies are found in [3] [10] [13] [15] [16] [18] [19] [20] for different countries. These values are updated and adapted to the case of China. Standard deviations from wind and solar intermittency are calculated based on average capacity factors from the SWITCH-China model. We assume that risks are independent except for fuel costs where covariance values are non-null, consistently with the literature. Projections for future carbon price trajectories range from \$0 and \$115/t-CO_2 in 2050 [18].

Hereafter, the term 'portfolio' (and corresponding costs and risks) designates the average annual power generation level of each of the six technologies mentioned above. It does not include generation from technologies not developed after 2015. The terms 'SWITCH', 'LP', and 'cost minimization' designates the first step of the methodology, while 'QP' and 'risk minimization' are used to represent the second step.

B. *Risk minimization of portfolio in year 2030*

First, the QP risk minimization is applied to the year 2030 only. Average annual electricity demand that must be met by the six technologoes in 2030 is projected to be 4300 TWh.

The SWITCH least-cost portfolio, Ps, characterized by x_{2030}, presents an average electricity production cost of \$72.60/MWh and a risk on cost of \$15.80/MWh. Its carbon emissions for the year 2030 add up to $2.24*10^{09}$ tons. By allowing the generation level from each technology to vary within plus and minus 15% around their SWITCH least-cost generation levels, the QP identifies least-risk portfolios, subject to the set of constraints presented in the previous section. For a given costs the corresponding energy mix with lowest risks is called the Pareto efficient portfolio, or *efficient portfolio*. In Figure 2, the Pareto efficient frontier (left branch of the black curve) correspond to all efficient portfolios with costs ranging from \$72.63/MWh to \$73.47/MWh.

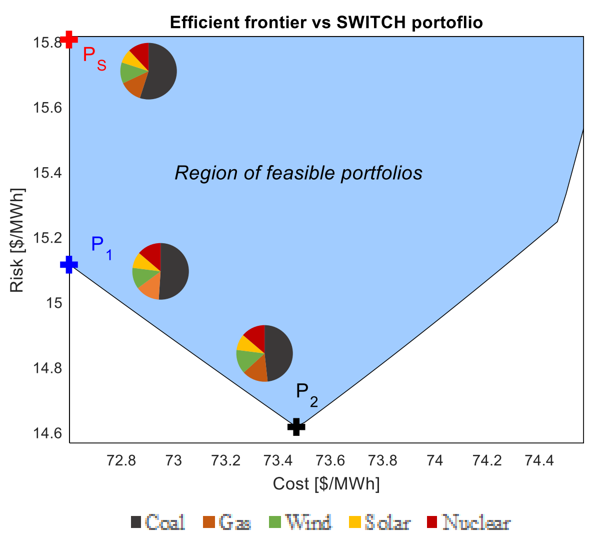

Figure 2 Feasible portfolios and frontier of Pareto efficient portfolios, displayed by expected LCOE and standard deviation of LCOA, for the year 2030 (QP optimization). Red-cross represents the SWITCH portfolio P_S. Pie charts represent generation shares for the six technologies in portfolios P_S, P_1 and P_2.

We distinguish two notables Pareto-optimal portfolios: P1 and P2. P1 is the least-cost efficient portfolio, presenting slightly higher costs than the non-Pareto efficient least-cost portfolio P_S identified by SWITCH. P2 is the feasible portfolio with lowest risks. By definition, it is a Pareto efficient portfolio. In this particular case, P_1 also meets the condition below:

$$\min_{P_i} \left(Risk(P_i) - Risk(P_S)\right) + \left(Cost(P_i) - Cost(P_S)\right) \quad (11)$$

The composition of electricity mixes between P1 and P2 do not considerably vary between each other, as the QP optimization is limited around 15% of SWITCH generation levels.

Two factors induce the changes in power generation levels made by the QP compared to SWITCH least-cost mix. The first one result from energy systems that have high LCOE – penalized in the SWITCH optimization – but low standard deviations – favored in the QP. The second factor is the positive impact of diversification on decreasing risks: even the addition of a risky technology in the energy mix can, under some conditions, lower the overall risk of the portfolio.

Changes induced by the risk minimization approach for China's 2030 electricity mix vary between -169.6 TWh (coal) and +77.2 TWh (nuclear) for P_1, -288.8 TWh (coal) and 83.4 TWh (gas) pour P_2, as shown in Figure 3. The total change in generation source across all technologies compared to Ps is 8% for P_1, 13% for P_2. In practice, this results in a higher change in installed capacity for renewable energies than thermal energies, because of the limited capacity factors for wind (national average is 0.18 [19]) and solar systems (national average is 0.19 [20])

Coal steam turbines have low average LCOE in China compared to other technologies, which makes them a preferential energy source by cost-minimization models. However, the uncertainty on future coal prices and on future CO_2 emission regulations, significantly impacts the variance of coal steam turbine LCOE. For this reason, and because of the effect of diversification, the coal share in all efficient portfolios including P_1 is decreased compared to Ps, as coal is by far the dominant source of power in the SWITCH portfolio. P_1, the Pareto-optimal portfolio with lowest costs, generates more electricity from coal than the other Pareto-optimal portfolios. Following the same reasoning, the share of natural gas is increased in Pareto optimal portfolios compared to Ps. While gas is greatly increased in P_2, its high costs in China do not make it a good candidate when costs are limited, therefore its share is only slightly increased in P1 compated to Ps. The larger the reduction in coal and increase in gas, the lower the total variance of the corresponding efficient portfolio. For the same reason, the small share of solar PV is increased up to its maximum (+15%) compared to the SWITCH results in all efficient portfolios. On the other hand, the relatively high cost and variance of wind and large share compared to solar in P_S do not make this technology a good candidate for risk minimization when total cost is limited. In all portfolios on the efficient frontier, conventional nuclear reactor technology is increased up to its maximum in the QP optimization.

In all efficient portfolios, increase in renewable generation resulting from the risk optimization is higher than increase fossil-fuel generation, despite the cap on wind and solar shares as a function of gas share to maintain grid operability.

The cap on CO_2 emissions is not an active constraint in any of the Pareto-optimal portfolios. Therefore, accounting for risk on costs leads, in the case of China, to a reduction in carbon emissions compared to a simple cost minimization.

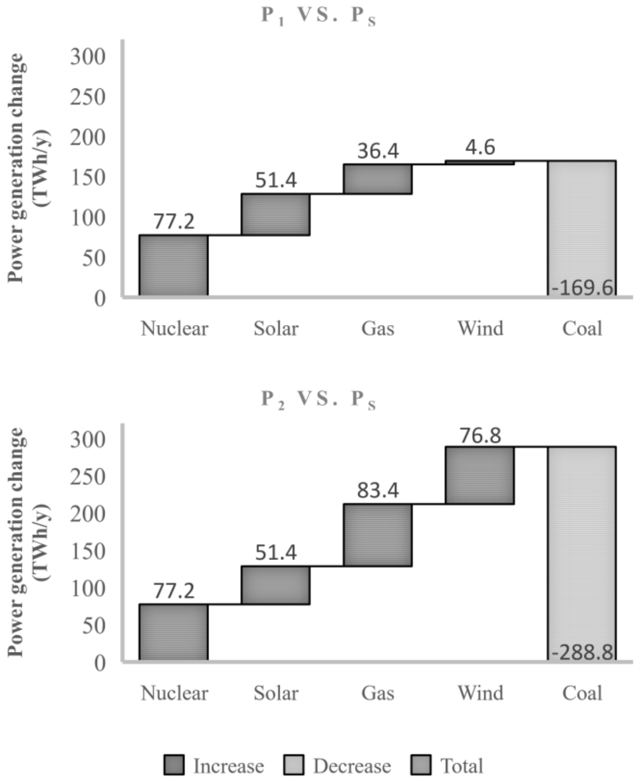

Figure 3 Annual change in electricity generation per technology for the two efficient portfolios P1 (top graph) and P2 (bottom graph) compared to the SWITCH portfolio for the year 2030.

Any of the portfolios between P_1 and P_2 could be favored over P_s by policy makers, depending on their level of risk-aversion, i.e. on how much they are willing to increase the costs from the least-cost portfolio in order to reduce the uncertainty on costs.

Choosing P_1 or P_2 instead of the least-cost portfolio would have the following consequences on overall risks and costs (Table 2):

TABLE 2 CHANGE IN 2030 COSTS AND RISKS FOR EFFICIENT PORTFOLIOS P1 AND P2 FROM LEAST-COST PORTFOLIO PS

	Total change in costs in \$/year (%total cost)	**Total change in risks in \$/year (%total risk)**	**ΔCost + ΔRisk in \$/year**
P_1	$+1.43 \times 10^8$ (0.46%)	-3.04×10^9 (-4.49%)	-2.90×10^9
P_2	$+3.72 \times 10^9$ (1.19%)	-5.10×10^9 (-7.52%)	-1.38×10^9

P_1 demonstrates smaller changes in cost and risk than P_2. Any portfolios on the efficient frontier between P_1 and P_2 would yield a decrease in risks on costs of at least \$3.04 billion/year and at most \$5.10 billion/year. In this case, all efficient portfolios yield higher decrease in risks than increase in costs compared to the original least-cost portfolio, and can therefore be of high value for energy planners.

C. *Risk minimization over time and impact of introducing a new technology on overall risk*

The efficient frontier of an electricity mix evolves over time for two reasons in our model. First, the overnight costs of some technologies – here, wind turbines, solar PV and coal CCS – are assumed to decrease in the future following R&D programs and gain in experience. This learning curve impacts both the LCOE value and its standard deviation. Second, the introduction of a new technology – coal CCS – from 2035 on impacts the SWITCH optimization, the Hessian matrix and the constraints of the risk optimization.

The QP is run over the four ten-year long periods of SWITCH. In all years, changes induced by risk minimization lead to lower carbon emissions. However, Figure 4 shows that the magnitude of this change varies according to the initial least-cost mix in each year. In period 1, maximum allowed deviation are binding constraints for wind, solar and nuclear, limiting the potential for carbon emissions reduction. In the third period, decarbonization is favored by the risk on carbon price, which leads to a high decrease in carbon emissions between PS and efficient portfolios. In the fourth period, projected carbon regulations result in an optimal SWITCH portfolio that is cleaner than in previous periods, therefore the following impact of risk minimization on emissions reduction is relatively lower.

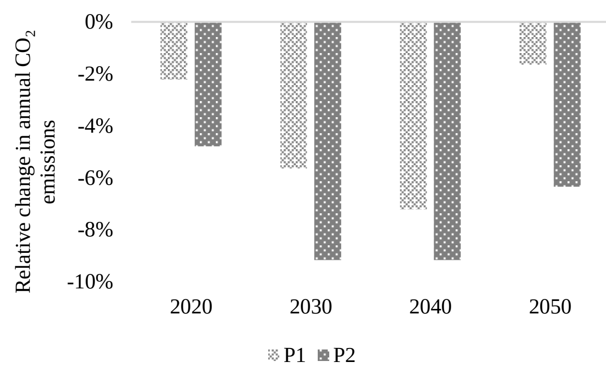

Figure 4 Annual change in carbon emissions for the two efficient portfolios P1 and P2 compared to the SWITCH portfolio.

At time of first implementation, in 2035, the optimal generation share of coal with CCS equals 4.5%, and the share of coal 30%. A hypothetical situation where these 4.5% would instead be additional conventional coal leads to an increase in total portfolio risk on costs of 1.75% or \$0.92 billion per year. Although coal with CCS shows significantly higher variance on technology cost than conventional coal, the advantage of coal CCS against carbon price uncertainty makes it a valuable asset to decrease overall risk on costs in the mix.

IV. CONCLUSION

In all four periods from 2015 to 2054, we find that it is possible to create portfolios within plus or minus 15% around the least-cost portfolio generation levels that show lower risks on generation costs without significantly increasing the costs.

While the specific portfolio choice depends on policy makers' aversion to risks, any of the efficient portfolios should be favored by policy makers willing to increase generation costs of least-cost portfolios from conventional LP tools, provided that it yields a reduction in risks higher in amplitude.

Despite nuclear power's costly safety regulations and risk of accidents, its low costs and relatively low share in China give this technology a key role in reducing financial risks over the 2050 horizon. Wind and solar are favored in latter periods, while the share of gas is mostly increased in the first two periods, despite its emissions, high costs, and high variance. The increase in gas share is a new phenomenon in reality, currently observable in the Chinese power sector. In all periods, risk minimization leads to a decrease in coal, although at no time is carbon cap a binding constraint. Uncertainty on the possibility of a carbon regulation can significantly increase the share of renewable energies, therefore reduce the CO_2 emissions, of an energy mix even without the actual implementation of regulations. As a consequence, the transition to a clean power sector occurs earlier with a risk minimization than with a cost minimization. The 'fear of regulation' can be seen as a first step towards the reduction of greenhouse gas emissions.

This analysis shows that, while cost-minimizing modeling tools provide a valuable insight into the nature of the future energy mix that policy makers seek to plan, it should only constitute the first step of a thorough energy planning procedure. Reliable sources from which policy makers obtain cost projection data usually provide standard deviations, error bars, or other metrics to represent the uncertainty on the validity of their projections. While cost-minimization models only use half of the available information – the expected value – the other half can be used, with not much additional effort, in the two-step methodology we presented.

On the short term, our two-step module makes the transition easier for policy makers, since it integrates well with existing, 'legacy' linear tools. Compared to simple cost-minimization, this two-step optimization process provides, at low costs, a more accurate picture of future consequences of energy planning decisions and on levers to strengthen energy affordability.

However, the two-step process has several limitations. The somewhat arbitrary maximum deviation value, set at 15%, aims at maintaining the reliability of the grid ensured by the LP in the absence of short time scale consideration in the QP. Yet, such consideration would also allow for including storage in our analysis, especially useful for calculating risk on costs resulting from renewable intermittency. Moreover, changes induced by the risk minimization may contradict one of the LP constraints. This two-step process is therefore suboptimal compared to a model that would optimize costs and risks in a single step. The use of mean-variance optimization creates one, well known, caveat: the hypothesis of normally distributed costs and quadratic utility function of stakeholders. Methods using more specific risk measures than the standard deviation could be implemented in the risk minimization step, however there is a crucial trade-off between increasing solution accuracy and increasing computing time.

In the longer term, the objective is first to integrate these two steps into a single tool, a 'super-SWITCH' model optimizing costs, risks, and hourly dispatch, and second to encourage policy makers to adopt this higher-fidelity model instead of the existing limited cost-minimization tools.

ACKNOWLEDGMENT

The authors thank Areva and the Karsten Family Foundation Endowment for their support.

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