Analytical Methods for the Study of Investment Strategies in Compliance with Environmental Policy Requirements

Final Project Report

Power Systems Engineering Research Center

Empowering Minds to Engineer
the Future Electric Energy System

Analytical Methods for the Study of Investment Strategies in Compliance with Environmental Policy Requirements

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Power Systems Engineering Research Center

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Executive Summary

Investment in new generation capacity is critical to maintain the power system's capability to provide reliable and economic electricity to meet the growing demand. For individual generation companies, correctly-timed investment into the appropriate generation technology located at the appropriate site will yield a future stream of beneficial returns over many years to come. Conversely, a misguided investment could lead to unforeseeable and undesirable consequences that not only negatively impact the profitability of the company but also may compromise the reliability of the power system. The pursuit of an effective strategy to formulate profitable investment plans has been one of long interest, yet many existing strategies have limited capability to address some significant challenges. A particularly good example is the inability of many current approaches to explicitly consider the compliance requirements imposed by various environmental policy legislative and regulatory initiatives so as to reduce the environmental impacts of electricity operations. Moreover, uncertainty on both demand side – short-term load variations and long-term growth patterns – and supply side due to the deeper penetration of the variable and intermittent outputs of renewable energy resources introduces major complications in the quantitative measure of the risk and return associated with the investment. The additional sources of uncertainty in the competitive environment further complicate the analysis due to the interactions of the independent decisions of the various market participants and their impacts on grid congestion and the outcomes of transmission constrained electricity market. The objective of this project is to effectively address the many complicating factors in the investment decision-making area with the explicit consideration of the impacts of environmental regulations and of key sources of uncertainty. To meet this objective, we constructed an appropriate analytical framework to facilitate the analysis of the issues so as to lead to the selection of improved investment decisions.

The proposed analytic framework provides the capability to assess the profitability of the investment decision over a longer period by taking into account the ramifications under the considered sources of uncertainty and directly incorporating the compliance requirements of environmental restrictions. The framework makes detailed use of probabilistic and scenario analysis so as to quantify the uncertain outcomes. For example, the methodology can quantify the returns on an investment in intermittent wind generation turbines as well as those on a coal-fired generation unit investment under the various environmental restrictions that impact its operations. Furthermore, the framework is effective in the analysis of *what if* questions to study the impacts of a large number of issues, such as various transmission expansion alternatives, implementation of significant wind generation projects by a competitor generation company, and termination of production tax credits for renewable energy generation.

The modeling framework has a three-layer structure. The decision maker interfaces with the optimization layer through the input of a set of candidate investment plans. The information flow among the three layers allows the comparison of the various alternatives on a consistent basis in line with the decision maker's preferred tradeoff criteria between risk and return in terms of expected value, or worst scenario or maximal regret. The assessment layer analyzes comprehensively each investment plan under the represented sources of uncertainty. The computational engine in the operations and market layer simulates the clearing of the hourly transmission-constrained markets by solving the DCOPF formulation for the market clearing problem. In this way, the analysis explicitly accounts for temporal and spatial correlation among the loads and renewable resource outputs under transmission network constraints. Also, the analysis considers the impacts of the retirement of generation capacity, addition of new capacity, transmission expansion, and load growth. Indeed, the framework allows the ranking of the various alternatives in terms of specified metrics on a meaningful basis. The framework is a practical decision tool to help both planners and investment analysts to make better-informed decisions by explicitly taking into account various sources of uncertainty and the requirements of compliance with environmental regulations.

We illustrate the application of the framework with numerical results from representative case studies carried out on the 240-bus WECC test system. Our studies indicate the effectiveness of the analysis of the decision alternatives by the three-layer framework so as to effectively construct an investment plan in line with the decision maker's preferences. The studies show the sensitivity of alternatives to the technology type, implementation timing, siting location, and generation capacity addition. Results using the proposed framework, with proper visualization, reveal insights into the consequences of an investment plan that could not have been available without the framework. The case study results are particularly useful to understand the impacts of each individual investment company's strategy on the power system's overall generation adequacy in meeting the forecasted loads and in the resulting market performance. The report discusses in detail the analytical basis for the framework, analyzes the case study results and provides an interpretation of the ramifications of investment decisions made with the developed framework. The report also provides directions for future work.

Student Theses: Yanyi He, "Analysis of investment decision making in power systems under environmental regulations and uncertainties," PhD dissertation, Iowa State University, expected September 2013.

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1 Introduction

The push toward a cleaner and more sustainable environment is bringing on new pressures on the electric power industry. The numerous fossil fired power plants that operate today create the largest fleet of stationary carbon dioxide (CO_2) emitters. There are many climate change initiatives, in various stages of development, whose implementation will strongly influence the future course of the industry and consequently the entire nature of electricity planning and future operations. Similarly, the issue of clean water is an equally critical concern and the subject of past and future legislation and regulation. The various initiatives aim to reduce the environmental footprint of the electricity sector and will entail fundamental changes in the way power systems operate, the role electricity customers play and the scope and nature of future resource investments. In the restructured, competitive environment, in distinct contrast to that of the vertically-integrated utility industry, the generation and transmission planning decisions are undertaken by different entities, on an increasingly decentralized basis. Such decisions are subject to the constraints imposed by the existing climate change initiatives, a patchwork of mandates, incentives and voluntary programs – as well as all those by the myriad initiatives underway, each with it distinct targets and goals. These developments impact the planning environment significantly since they introduce various additional sources of uncertainty that further complicate the investment decision-making process. This report summarizes the work on our project that focuses on the setting up of a systematic approach to investment decision making with the explicit consideration of the impacts of compliance with the environmental requirements already implemented or those that are under consideration.

The basic objective of this project is to study the formulation and solution of investment decisions in new generation resources that are compliant with the requirements of environmental policies and explicitly consider their attendant uncertainty. Environmental policies take various forms and influence resource investment decisions in different ways. For example, the creation of renewable portfolio standards (RPS) requires a specified fraction of the load and/or energy be supplied by renewable resources by a defined date has resulted in the growing push to implement renewable energy projects at deeper penetrations. Other legislative acts, such as a carbon tax, the provision of production/investment tax credits and the implementation of time of use pricing, create incentives for compliance with policy goals but need not mandate such actions. The legislatively improved introduction of a carbon cap-and-trade mechanism and the use of renewable energy certificates via legislation sets up new markets to implement a flexible structure for meeting the goals of reduced greenhouse gas emissions. Such structures provide individual power producers the flexibility to trade emissions allowances among themselves and provide incentives to some to install improved abatement technology. The policies, be they mandates or voluntary or market-based, measures influence planning decisions to a huge extent. They may create unparalleled opportunities for the investment in renewable resources or may force the resource owners to create cleaner generation sources than ever before. Moreover, they create new opportunities and challenges in the planning and operations of power systems and in the effective investment decision making process.

A salient feature is the need to explicitly consider the broad range of uncertainty associated with the repercussions and ramifications of such environmental policies. Such consideration is very important in the framing of investment decisions and results in the addition of complications to what is already a very complex decision-making process. In this report, we provide a detailed summary of the methodology development and demonstration of its application to realistic power system test cases. We devote the remainder of this chapter to set the context within which our work is developed, provide a brief survey of the state of the art and delineate the key requirements for the methodology.

1.1 Need for additional investments in the era of new environmental legislation

Electricity demand is expected to grow continually and steadily for decades to come. In the EIA Annual Energy Outlook 2013, forecasts indicate that electricity consumption will increase by 28% from 2011 to 2040 at approximately 1% per annum rate[7]. To accommodate such growth in electricity demand, new capacity of electricity generation must be built at a pace that meets or exceeds the growth of demand and retirement of old generators to maintain power system reliability. The additions of capacity must be done in a way that the reliability of the power system is appropriately maintained.

The North American Electric Reliability Corporation (NERC) considers reliability to consist of the system adequacy – the condition that sufficient resources are installed to provide customers with a continuous supply of electricity to meet their demands – and security – the ability of the bulk power system to withstand sudden, unexpected disturbances. A prerequisite for adequacy and security is that the system has available capacity at all times that exceeds the demand. The assurance of reliability becomes considerably complicated in the era of the many new requirements that must be met as a result of new legislation and regulatory initiatives and decisions. We next review the nature of these requirements.

Numerous environmental regulations have been imposed on the electric power industry, which was responsible for 33% of greenhouse gas emissions in the U.S. in 2011[9]. Such regulations have imposed additional considerations to be taken into account by investment decisions makers. The following discusses three representative requirements that impact investment decisions.

Cap-and-trade policy The policy constrains the aggregate emissions of polluting electricity generation resources. The limit or cap is either administratively allotted or sold via an auction to generator owners in the form of permits or allowances to emit or discharge specified amount of pollutants. The number of allowances represents the required cap on a pollutant. Any violation of emissions beyond the allowance is subject to penalty. Excess allowances may be banked, used to offset pollution emissions of other facilities or traded in markets of emission allowances. The expenses of emission allowances introduce additional costs of the energy by polluting resources. The cap-and-trade policy imposes limits on the production quantity as well as the price competitiveness of generation from polluting resources. Regional greenhouse gas emissions (RGGI) [6] is the largest voluntary CO_2 cap-and-trade program in the U.S, with nine states involved. California also started its own CO_2 cap-and-trade program in December, 2012 [1].

Carbon tax A tax is imposed on the CO_2 content of fuels used for energy and production so as to explicitly represent the costs of the emissions by a polluting generation unit. The implementation of carbon tax is simple and bypasses the need to set up new market structures. Many economists believe such tax to be efficient means for CO_2 reduction. The carbon tax policy has been implemented in some countries like Switzerland and Australia, but has not been adopted by large carbon-based electricity generation nations such as U.S. and China.

Renewable Portfolio Standards The standards specify minimal renewable generation targets to be provided by renewable resources by prescribed dates [5]. Such standards impose these obligations on electricity supply entities, such as investor-owned utilities and electricity service providers. Qualified renewable energy production may earn certificates for every unit of electricity injected into the grid that indicate compliance with the obligations. RPS are mandatorily or voluntarily imposed in more than 29 states in the U.S and the District of Columbia.

The thrust of numerous environmental legislation efforts is to either directly restrain the pollutant emissions via a cap-and-trade policy, or carbon tax or to promote investments into new renewable technology projects so as to satisfy RPS requirements. As electricity demand grows continually, renewable generation to meet load must be increased commensurately. There are various other regulatory mechanisms, such as feed-in-tariffs for the purchase of excess renewable energy injections by residential or small commercial customers, to further promote these objectives. The ultimate goal goes beyond the reduction of emissions and the deeper penetration of renewable generation resources into the grid to make the future power grid a sustainable system to meet effectively future customers' energy requirements.

The compliance with environmental policies imposes requirements in the planning of future systems. Under current environmental policies, generation companies must either retire much of the coal-fired generation resources or make large investments in pollution abatement technology. However, investment in renewable generation projects, with their large amount of capital and land requirements, may be attractive alternatives. The deeper penetration by renewable resources poses daunting challenges to manage the intermittency and variability nature of the outputs and the integration issues with the provision of ancillary services. In addition, the expansion of the transmission grid to assure the deliverability to the grid of the added renewable generation is a critically important challenge that must be explicitly considered in the planning work. Clearly, the requirements imposed by environmental legislation introduce many new complications into planning. Moreover, the enactment of future environmental legislation and the introduction of new regulatory initiatives are difficult to predict accurately and are subject to a wide rage of uncertainty sources. Such uncertainty must be considered, consequently, in the planning and investment decision making. The following section discusses additional sources of uncertainty and their categorization.

1.2 Sources of uncertainty

Planning and investment decision making, by their very nature, deal with the uncertain future. As is well known, the power system is subject to many sources of uncertainty. The deepening penetration of renewable resources has introduced additional sources of uncertainty which must be considered in planning and investment decision making. We discussed in the previous section the uncertainty associated with the impacts of environmental legislation. We classify the sources of uncertainty may be classified into the categories of aleatoric and epistemic uncertainty[25].

Aleatoric uncertainty is intrinsically random and cannot be eliminated or reduced through more accurate measurements; however, the uncertainty is statistically quantifiable. Therefore, aleatoric uncertainty is also known as statistical uncertainty. For instance, wind speed uncertainty is aleatoric, because each measurement of wind speed at a given location at a given time point is physically obtainable. Moreover, the average wind speed may be statistically estimated from all the collected measurements. Other examples of aleatoric uncertainty that are relevant to the investment decision making process include electricity demand, both short- and long-term, power output from renewable energy sources, forced outages of generation units and transmission lines, weather conditions and the economic situation.

Epistemic uncertainty arises from factors we may know but, in practice, we do not. Specific reasons for such uncertainty may be because we cannot measure with sufficient accuracy the phenomenon of interest or the information is kept confidential. Therefore, epistemic uncertainty is also known as systematic uncertainty. For instance, the generation investment decisions of other firms constitute confidential information and so the probabilities associated with such decisions are unknown. Thus, their investment decisions constitute an epistemic uncertainty. Other examples of epistemic uncertainty that are relevant to the investment decision making process include: government policies, technology breakthroughs, economic conditions and investment decisions made by other entities.

This classification of uncertainty sources useful as it helps us to determine the approach to deploy for probabilistic risk assessment and to collect the appropriate data. For epistemic sources of uncertainty, we identify meaningful scenarios under which we assess both the likely and the high-impact realizations of uncertainty. For aleatoric sources of uncertainty, we approximate their cumulative distribution functions (c.d.f.s) from past data and use probabilistic methods to estimate the expected values of the metrics of interest.

1.3 Resource characteristics and investment decisions

This section provide a brief review of supply-and demand-side resource considerations in investment decisions. The investment decisions in this report are made in the context of the existing power system. As such, in undertaking every investment decision, the salient characteristics of both supply and demand resources and the interactions of each resource with the existing resource mix must be explicitly considered.

Table 1: Brief economic comparison of generation technologies

Technology	Advantages	Disadvantages
OTEC	renewable resources; long life times; zero fuel cost	extremely high investment costs; low capacity factor
IBGCC	low CO_2 emissions; high efficiency;long life times	no significant drawbacks
nuclear	zero emissions; high efficiency	long lead times; nuclear waste issue
NGCC	high efficiency; constant output	moderate emissions
oil	high efficiency; constant output	very high operations cost; intensive emissions
solar PV	renewable resources	large land requirements
geothermal	renewable resources; very long life times	high investment cost
solar thermal	renewable resources; possible 24-h supply source	heavy water usage requirements
MSW	renewable resources; waste-to-energy; reduces needs for landfills	high operational costs
hydro	renewable resources; low operations costs	scheduling complexity
onshore wind	renewable resources; zero operations cost	require large land
offshore wind	renewable resources	high investment cost; longer lead time
IGCC	high efficiency output	high emission rate; high operations cost
wave Power	renewable resources; predictable output	high investment cost

Table 1 provides a listing of the key economic advantages and disadvantages of some common generation technologies.

The analysis of resource addition alternatives requires careful weighting of the investment – fixed – and operations – variable – costs of a resource. Compared to renewable resources, the operations costs of fossil-fuel fired generation are high and increase under both a carbon tax or cap-and-trade policy. Carbon sequestration technology can reduce the carbon emissions, but entail additional investment costs for the retrofit. Investors can choose to either choose retire or retrofit an existing fossil-fuel fired generator. In light of environmental policies, gas-fired generators and renewable generators are key expansion alternatives in the next decade. Gas-fired generation has lower emission rate than other fossil-fuel-fired units, such as coal-fired and distilled oil units, and the current glut in low price gas supplies makes gas-fired resources a viable investment alternative. Renewable resources entail considerable upfront investments and typically, large area requirements for their installations. Their highly uncertain variability and intermittency nature is a key disadvantage. The available rebates and PTCs lighten the costs and their zero fuel costs are advantages. The next two years have brought down steep reductions in the cost of wind and other technologies. For example, PV costs have declined steeply in the past two years [4],[34]. Actually, the levelized costs of the same renewable technology may vary at different locations due to state and local policies, land costs and other factors. Storage technology has the ability to smooth the fluctuations of intermittent energy [15],[21],[27]. Storage acts symbiotically with renewable intermittent generation and can be an effective coupling to manage the intermittency issues.

In addition to supply-side alternatives, demand has considerable promise. The Federal Energy Regulatory Commission defines demand response (DR) as “changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized. [26]” The effective deployment of DR resources is a topic of wide current interests.

In our project, we make use of some of the common technologies as investment candidates and weigh the cons and pros of these technologies in the competitive markets and in maintaining compliance with the environmental policy requirements.

1.4 Review of the literature

There is a rich body of literature on investment decision making in power systems, including generation expansion and transmission expansion. The past publications have specific foci and address certain challenges of the investment problem. The following is a brief summary and discussion of several previous studies of highest relevance, particularly those that use optimization, game theory, or other mathematical programing approaches.

Several environmental policy regulations have been studied in the context of generation expansion planning. Linares et al. [22] presented the first model to incorporate three markets – energy, emission trading and green energy certificates markets – in an oligopolistic generation expansion planning problem. He et al. [19] compared the effectiveness and efficiency of carbon tax and cap-and-trade policies using several criteria in a generation expansion background. Zhou et al. [36] studied a policy design problem to promote investment in renewable energy in a centralized generation expansion setting under RPS and tax/subsidy policies.

Some studies use game theoretic models to account for market competition in the restructured power systems. Pozo et al. [28] integrated transmission expansion, generation expansion and pool-based market operations in the framework using a three-level mixed integer problem. The transmission expansion planning is charged by the system regulator at the upper level, subject to the Nash equilibrium of generation capacity expansion at intermediate level and equilibrium of the pool market at the lower level. Other studies avoided game theoretic models and used more computationally tractable optimization models to address generation and transmission expansion problems in a centralized decision-making framework. Sharan and Balasubramanian [31] studied a centralized integrated generation and transmission expansion problem, in which a centralized decision maker decides future expansion of transmission and generation at the same time subject to fuel transportation constraints. Bakirtzis et al. [10] considered three types of horizons in the model-short term operations, mid-term scheduling decisions and long-term cost-minimization planning in a vertical market structure. The environmental considerations were presented as costs of allowances and penalties.

Uncertainty is addressed in various ways by different authors. Roh et al. [30] studied the competitions and interactions among generation and transmission companies under uncertainty in generation expansion and transmission expansion planning. The Monte Carlo simulation method is applied to generate scenarios, and a scenario reduction techniques is introduced to reduce computational burden. Tekiner et al. [33] computed the Pareto front of expected values of system cost and air emissions for a multi-period long-term generation expansion planning under uncertainty of demand and distribution line outages.

We summarize the achievements and limitations of previous work in Table 2, which compares the contributions and features of the above mentioned studies from several perspectives. These perspectives are defined and interpreted as follows.

Granularity Investment decisions have a natural focus on long-term implications. But in order for the quantitative analysis to accurately reflect reality, short-term constraint also be included in the simulation model. The modeling resolution in existing literature ranges from hourly power system operations to abstract representation of yearly trend in the market.

Role of time Single period planning is usually computationally tractable and provides a big static picture of power system performances and decisions. To compensate the loss of dynamics, single period planning adds details to the formulation. The decision makers can model the development and evolvement by using multi-period planning, but might compromise the comprehensiveness of the formulation for the sake of computational tractability.

Deterministic or probabilistic formulation Deterministic optimization of expansion planning ignores the many sources of uncertainty faced in long term planning. Probabilistic formulation or sensitivity analysis provide more insights of planning with respect to accurate projections of the power system.

Transmission Electricity delivery is constrained by the transmission topology and capacity. A comprehensive investment plan consider congestion effects by existing transmission capacity as well as potential transmission expansion projects in the future.

Market In the restructured electricity market, generation expansion planning and transmission expansion planning are not centrally coordinated, neither are the generation expansion planning decisions made by different firms. Every power company has its own profit to maximize, but on the other hand, they are all in the game together, their decisions have direct and significant impact on each other, often in ways that are sophisticated and unforeseeable.

Environmental constraints Special modeling effort is required to incorporate environmental policies into investment decision making, because they affect the profitability of an investment strategy to a great extent. Policies can be modeled by additional constraints or adjusted objective function or cost parameters. For example, RPS is a mandatory policy; carbon are voluntary; PTC provides incentive; there are also markets for the trading of allowance or certificates. Modeling the details of some complicated policies by itself can be a challenging task.

Solution methodology and computational tractability Simpler models are more computationally tractable and scalable to larger-scaled systems. On the other hand, more complex models are able to capture

Table 2: Summary of relevant literature

Literature	granularity & time	transmission	policy	market	uncertainty	computation
[22]	load blocks, multi-periods	no	certificate, trading	oligopoly	no	LCP
[10]	hourly,mid-time maintenance, multi-periods	no	REC	centralized	no	MILP
[28]	load blocks, single period	yes	no	oligopoly	no	MPEC
[30]	load blocks, multi-periods	yes	no	Gencos, Trancos	yes	MILP and equilibrium, heuristic
[33]	load blocks, multi-periods	yes	emission cost	centralized	yes	simulation
[19]	multi-periods	yes	cap-and-trade, carbon tax	oligopoly	no	LPCC
[31]	load blocks, single period	yes	no	centralized	no	MILP
[36]	single period	yes	RPS subsidies	centralized	no	nonlinear, bi-level, heuristic

more features of the market, such as strategic investment and bidding behavior and risk-based decision making, but require much more computational resources and applicable to small-sized case studies.

Table 2 summarizes previous studies on investment in power systems that use mathematical programming approaches. This summary also reveals the limitations of existing studies and motivates the proposed framework. Most studies have low modeling granularity, especially those that consider market competition, policies, or uncertainty. Consequently, the modeling results cannot accurately reflect realistic market operations. Moreover, most studies that include detailed formulation of day-ahead and real-time markets lack the capability to analyze the impact of uncertainty and market power exercise. The treatment of uncertainty is simple and based on unrealistic assumptions such as perfect information about probability distribution. The scalability of several models is significantly limited by the complexity of optimization or game theoretical models.

1.5 Contributions of the project

Motivated by the limitations of previous work for investment decision making in power systems, we have developed a new modeling framework. This new tool makes several contributes. It has a relatively high resolutions of details in power system operations, such as hourly load patterns, temporal and spatial correlation of wind power and demand. The model take the perspective of a profit-maximizing generation investor, and explicitly incorporates the impact of environmental policy requirements. Market competition among different generation companies are treated as a special source of uncertainty using scenario analysis. We represented the impacts of market outcomes under a wide rage of uncertainty sources in the modeling framework, and assessed the investments by computing all metrics of interest to provide quantification of cost effects of environmental policy requirement and other sources of uncertainty. The project provides the decision maker with a range of optimization criteria to accommodate different risk measures and risk tolerance attitudes or preferences. The framework is able to deploy a computational engine capable to be applied to realistically sized power grids.

The remaining sections of this report are organized as follows. We provide a detailed description of the modeling framework in Section 2, including the model assumptions, the formulation, functions and coordination on the proposed layers. Section 3 reports the results of our representative case study using the 240-bus WECC model. The case studies illustrate the ability of the project to assess effectively various candidate investment under different sensitivity cases. We provide concluding remarks in Section 4 that summarize over key findings and conclusions. We also discuss directions for future work.

2 Analytical framework

The framework was designed to answer two fundamental questions. First, for a given investment plan, how to assess its effectiveness? Second, for a given set of investment plans, how to compare their relative effectiveness? To address these two questions, our new framework was designed to consist of three layers, as shown in Figure 1.

- Layer I, which is the interface between the model and the investment decision maker, is the optimization layer. This layer takes a set of candidate investment plans from the decision maker and compares their relative profitability with respect to a pre-determined set of criteria. This layer addresses the second fundamental question.
- Layer II is the assessment layer, which takes a given investment plan and provides a quantitative assessment with explicit consideration of uncertainty. This layer addresses the first fundamental question.
- Layer III is the operations and market layer, which solves an OPF problem for a given set of network configuration. This layer is a computational engine of the modeling framework.

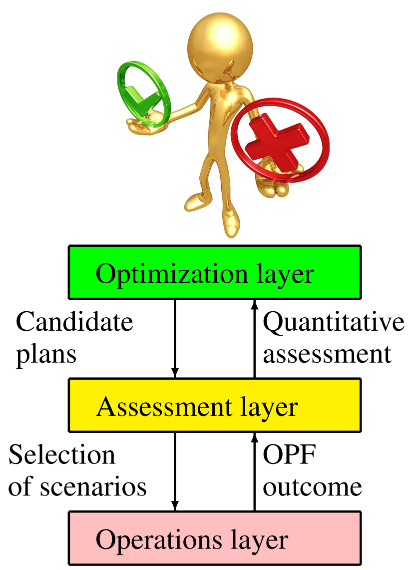

Figure 1: Framework

Details of the three-layer modeling framework are presented in subsequent subsections. This framework has the following salient features.

Objective We take the perspective of a specific generation company, which we refer to as the investing generation company, or iGENCO. The objective of the framework is to maximize the present value of the total profit of iGENCO over a given planning period (such as 20 years). The profit consists of revenue from sales of energy and tax credits less investment cost and operational cost. All revenue and cost terms are converted to current time to account for the time value of money.

Modeling resolution Several details of power systems are incorporated, such as load pattern, temporal and spatial correlation of wind power, and hourly optimal power flow.

Policy We model the effect of policy by adjusting cost parameters. For example, the production tax credits will reduce the variable cost of renewable energy generation, whereas a carbon tax will increase it.

Strategic behavior The strategic behavior of rival generation companies in the market is not directly modeled; rather it is treated as a source of epistemic uncertainty.

Uncertainty We adopt the categorization of aleatoric and epistemic sources of uncertainty and use different approaches to deal with the two types. For aleatoric uncertainty, probability density functions of random variables are assumed to be known, and we apply probabilistic analysis to quantify the impact of such uncertainty. For epistemic uncertainty, a set of relevant scenarios are assumed to be predetermined and we use scenario analysis to determine their impact.

Dynamics To simplify the model, the proposed model framework is a one-shot decision making tool, which can be updated on a yearly basis to incorporate new scenarios and probability distribution information.

Computation Three layers of integrated simulation models are designed as the computational engine of the framework, which is elaborated in the rest of this section.

2.1 Optimization layer

The optimization layer compares multiple candidate investment plans against a given set of optimization criteria. The input to this layer include a list of candidate investment plans and a set of optimization criteria. These input are provided by the investment decision maker. The output of this layer is a set of quantitative measures of all candidate investment plans against the criteria. The output information will help the decision maker to compare the risk and return of multiple investment alternatives against various risk measures.

The following are several commonly used optimization criteria.

Net present value of profit is the net present value of total profit (revenue from sales of electricity less generation cost and investment cost) throughout the planning horizon converted to the beginning of the horizon using an appropriate discount factor. Due to uncertainty in this net present value, the comparison between different investment plans require further analysis, such as the other criteria listed below.

Expected profit is probability weighted average profit over all scenarios. This is a common criterion for risk neutral decision makers. A major challenge is probability assignment to epistemic scenarios. Since no historical data are available to estimate such probabilities, subjective judgement will be used.

Standard deviation of profit measures the risk of the uncertain profit. The combination of expected value and standard deviation is commonly used to determine the tradeoff between return and risk of an investment. Projects with higher returns (expected profits) and lower risk (standard deviations) are considered more desirable than those with lower return and higher risk. The tradeoff between higher return with higher risk and lower return with lower risk is up to the risk tolerance, investment style, and personality of the decision maker.

Worse case profit is the expected profit under the worst epistemic scenario. This is a pessimistic risk measure for conservative decision makers. Similar philosophies have been used in robust optimization, in which the optimal solution is defined as the one resulting in the highest benefit under the worst case scenario.

Best case profit is the expected profit under the best epistemic scenario, the exact opposite criterion with the worse case profit. This is an optimistic risk measure for risk-seeking decision makers.

Expected maximal regret is the expected maximal regret under all aleatoric uncertainty. For two investment plans, say p^1 and p^2, and their profits under a scenario s^0, say $\pi(p^1, s^0)$ and $\pi(p^2, s^0)$, the regret associated with an investment plan is defined as:

$$r(p^1, p^2, s^0) = max\{\pi(p^1, s^0), \pi(p^2, s^0)\} - \pi(p^1, s^0) \text{ and}$$

$$r(p^2, p^1, s^0) = max\{\pi(p^1, s^0), \pi(p^2, s^0)\} - \pi(p^2, s^0).$$

The maximal regret associated with an investment plan refers to the maximal possible regret with respect to all possible investment plans:

$$max_p\{r(p^1, p, s^0)\} = max_p\{\pi(p, s^0)\} - \pi(p^1, s^0).$$

The expected maximal regret is the probability weighted maximal regret.

Intuitively, the smaller the expected maximal regret, the more likely the decision maker feels good about the selected investment plan under uncertainty.

2.2 Assessment layer

The assessment layer computes approximate probability distributions of a firm's profit over the planning horizon for a given investment plan. Inputs to the assessment layer include an investment plan, a set of scenarios for epistemic uncertainty, and a set of probability density functions for aleatoric uncertainty. The investment plan is passed down from the optimization layer, which uses the assessment layer as a sub-routine to assess all the candidate investment plan individually before it conducts a comparative analysis. The set of scenarios for epistemic uncertainty and a set of probability density functions for aleatoric uncertainty are assumed to be provided by the decision maker. The output of the assessment layer to the optimization layer is a set of approximate probability distribution functions under all epistemic scenarios.

The input epistemic uncertainty scenarios are subjectively selected by the investment decision maker to reflect what they perceive as possible, likely, and critical scenarios. The aleatoric uncertainty is assumed to be statistically characterizable using historical data. We assume that statistical characterization of the aleatoric uncertain parameters have been conducted and readily available to the assessment layer.

The output from the assessment layer are in the form of several quantitative indicators.

Profit capacity ratio calculates the generator's average profit per capacity over the planning horizon. The higher the ratio, the more profitability potential for further investment. This ratio helps decision maker to identify opportunities for better investment alternatives.

Annual profit distribution illustrates the probability density function of iGENCO's annual profit. The trajectory of such distributions over the entire planning horizon provides a convenient perspective to the company's profit outlook.

Total emissions indicate the environmental footprint of an investment plan. This value provides both an explanation for reward or penalty imposed by environmental regulations but also a projection of future reward or penalty as a result of potential policy changes.

Renewable generation portfolio measures the ratio between renewable electricity generation over total electricity generation from iGENCO. This is a similar indicator with total emissions.

Load curtailment is the total amount of demand energy not served due to lack of generation capability. This is a good indicator of the power system's generation adequacy and reliability.

System profit is the combined profit earned by all generation companies in the power system. This provides a comparative benchmark for iGENCO to evaluate its profitability against its competitors.

These assessment indicators not only provide the decision maker with a comprehensive assessment of the investment plans, but also shed light on directions of potential improvement.

2.3 Operations and market layer

The operations and market layer is a computational engine that solves a deterministic OPF for the entire planning horizon. Input parameters to the operations and market layer include transmission/generation capacity and availability, generators' supply function, deterministic fixed load, carbon taxes or credits, etc. These parameters are passed down from the assessment layer. The output of the operations and market layer is a sample path of the OPF solutions, which feeds back to the assessment layer. The sample path includes information such as hourly dispatched generations, local marginal prices and the power flows under a given scenario path through the whole planning horizon. The OPF formulation of the operations and market layer includes the Kirchhoff Current and Voltage Laws, capacity constraints, and implementations of environmental policies. The detailed formulation and assumptions of the operations and market layer are provided in Appendix B.

3 Case study

Our framework was tested on a realistic network on a planning horizon of twenty years. Section 3.1 describes the test systems, Sections 3.2 and 3.3 list the epistemic and aleatoric scenarios and candidate investment plans. Section 3.4 reports numerical results of the case study.

3.1 Test system

We use the reduced WECC (Western Electricity Coordinating Council) 240-bus network as our test system, which was developed by California Independent System Operators (CAISO) to use as a market design prototype [29]. It can be used as a realistic test system for California and WECC market. The 240-bus network evolved from a previous 225-bus network by conforming topology of areas outside CAISO shown in other transmission studies. The 225-bus network evolved from a 179-bus network by conforming topologies of CAISO shown in other transmission studies. There are 138 buses within CAISO excluding HOOVER. The network is enclosed, and no energy is transmitted in or out of the system, which means the facilities like power plants and transmission lines are all located within the system. The market comprises the whole network.

Figure 2 shows the topology of WECC network. The shaded blocks are the areas with CAISO generators. Each bus shown in the topologies may have multiple sub-buses with various voltages. It is worth to mention that the topology does not represent the physical geometry. The resources characteristics inherit from [29] are listed in Appendix C.

3.2 Scenarios in epistemic and aleatoric uncertainty

3.2.1 Generation of epistemic scenarios

Four epistemic scenarios were generated, where are described as follows.

$\mathbf{S}_0$: This is the baseline case, in which the generation companies (except CDWR, who has large hydro only) have barely enough renewable generation capacity to meet the RPS in California. We also refer to the transmission network in this scenario as the baseline transmission network, which includes 122 new transmission lines to be built throughout the planning horizon.

$\mathbf{S_C}$**:** This epistemic scenario was used to observe the impacts of a carbon tax policy. A carbon tax policy is assumed to be imposed on the power systems from year 9 in the planning horizon, since we assume the planning start in 2004, the first carbon auction was held in California in 2012 [1]. The carbon price started to be 10$/ton in 2012 and increased to 75$/ton in 2020 [8, 3, 18]. We assume that the carbon taxes remain constant within a year. The carbon auction mechanism is not explicitly modeled. The carbon price is predetermined to be $[13+2*(year-1)]*1.05^{2*(\text{year-1})}$ $/ton. Other conditions stay the same as baseline cases.

$\mathbf{S_T}$**:** This epistemic scenario was used to study the impacts of transmission lines. A new transmission expansion plan was assumed, and the investments of all generation companies (excluding investing generation company) are the same as baseline scenario. No carbon tax policy was assumed.

$\mathbf{S_{g\backslash c}}$**:** This epistemic scenario was created to observe the impact of optimistic system wide investment in renewable energy generation technology. The same carbon tax policy as in $\mathrm{S_C}$ was assumed.

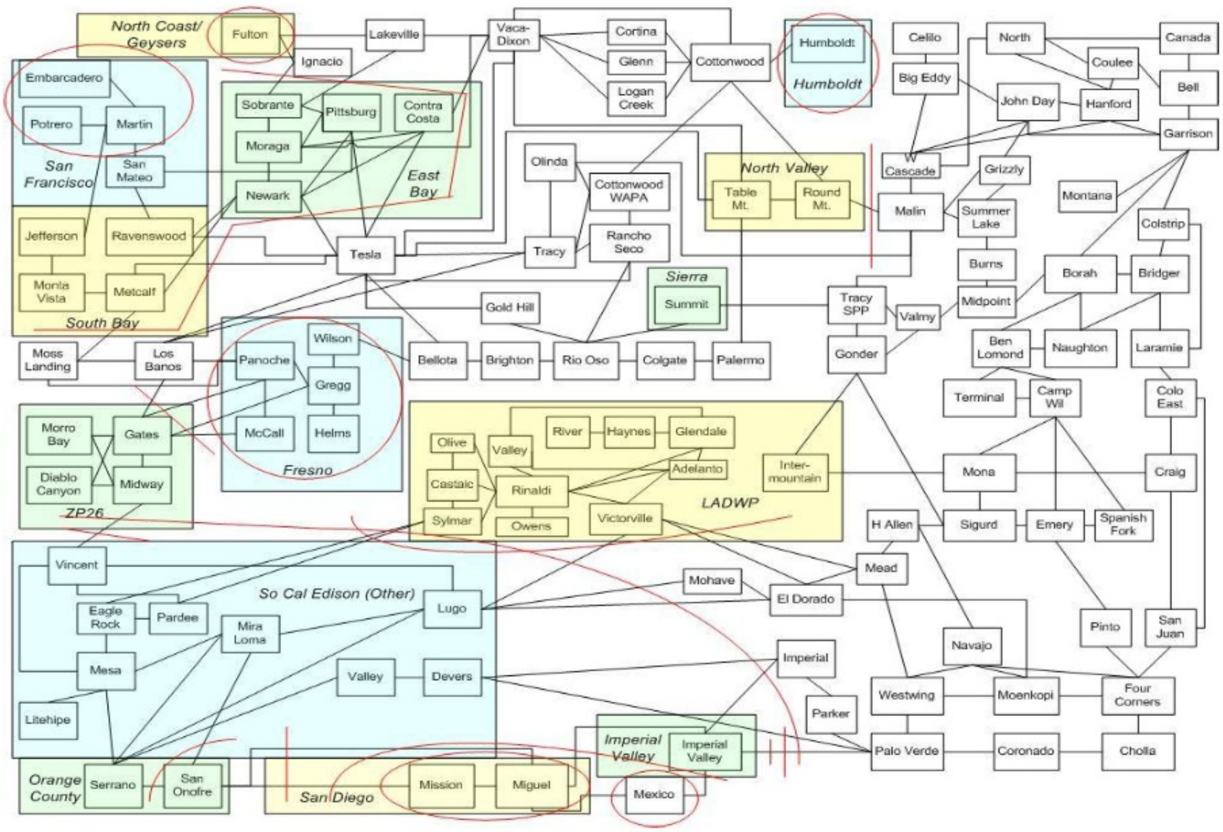

Figure 2: WECC 240-bus topology

3.2.2 Generation of aleatoric scenarios

We assume the electricity loads or renewable generations among seasons are independent. A week is the minimal unit for temporal correlations of loads and renewable intermittency. A season is decomposed into thirteen non-overlapping weeks. The electricity loads or renewable generations in the thirteen weeks follows the same distributions if there exists any. We also assume the outputs among the non-overlapping weeks are independent too. The scenarios under aleatoric uncertainty were generated in the following way:

1. As Figure 3 shows, we decompose a year into four seasons, and each season include 13 weeks. We pick one week at a time from the 13 weeks, and repeat 13 times to make a sub-scenarios. If 13 weeks are numbered from one to thirteen, by using polynomial theorem, distinguished sub-scenario probability follows equation $\frac{(\sum_i n_i)!}{\prod_i (n_i)!}$. Here, n_i is the number of times week i being selected. The sum of n_i in our case is thirteen. The number of distinguished sub-scenarios follows equation $\frac{(n+m-1)!}{n!(m-1)!}$, where n is the selection times, and m is the number of options in each selection. Both of them are thirteen. There are 5200300 sub-scenarios in a season. We assume seasons are independent with respect to renewable generation and electricity demand.

2. As Figure 4 shows, each red dot represents an independent sub-scenario in the corresponding season. Then we choose one sub-scenario from each season sequentially to compose a scenario to represent a whole year in the operations and market layer. In total, there are 5200300^4 scenarios. Those scenarios are viewed as realizations of statistical uncertainty with equal probabilities.

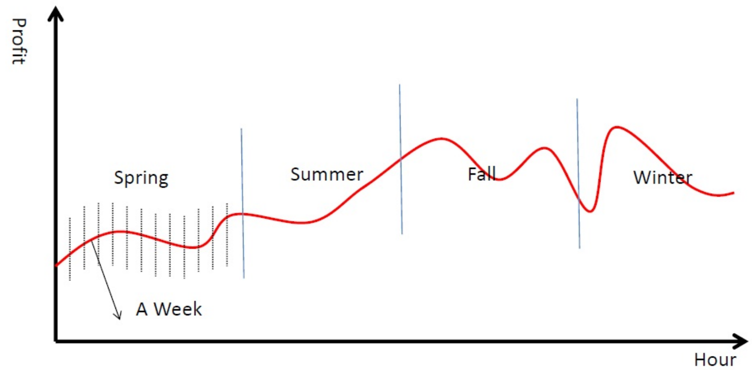

Figure 3: Scenario makeup process 1

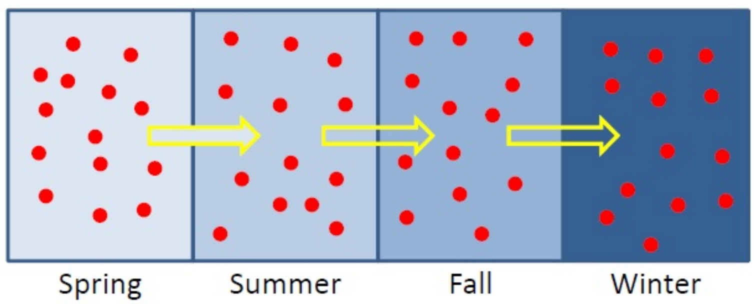

Figure 4: Scenario makeup process 2

3.3 Candidate investment plans

We select the largest generation company in the data set as the investing generation company for our case study. Although it resembles PG&E, our case study results do not necessarily reflect any reality with the company, since numerical results from our case study are obtained using various assumptions and unrealistic data. We will refer to the investing generation company as iGENCO, which is assumed to have rational and reasonable perceptions of other market players' decision making on investment and operations based on analysis of available public reports. The investing generation company follows the generator expansion assumptions described in Appendix E.

Plan A Also called the baseline investment plan, Plan A assumes that iGENCO has about 32.8% renewable generations. All types of possible technologies are being invested in. The investment capacities are assigned according to historical data.

Plan B This plan represents a strategy of heavy investment in renewable generation. The largest generation company iGENCO invests much more heavily in renewable energy generation than the RPS.

Plan C This is similar to Plan A except that all the investments were made one year ahead.

Plan D Unlike in Plan A, in which all types of possible technologies are being invested in, Plan D assumes that all investment in renewable energy generation is in wind.

Plan E In this plan, the locations of new generation capacity in Plan D are randomly changed in order to observe the impact of locational effect of investment strategies.

3.4 Computational results

3.4.1 Assessment of five investment plans under four epistemic scenarios

Table 3: Profit of five investment plans under four epistemic scenarios (billion $)

	Plan A		Plan B		Plan C		Plan D		Plan E	
S_0	34.43	0.3893	34.69	0.3903	34.84	0.4000	34.32	0.4058	33.42	0.3889
	54.65	22.09	54.96	21.96	55.38	22.43	55.24	21.22	54.14	20.98
S_C	45.88	0.4514	46.80	0.4494	46.00	0.4557	45.18	0.4582	44.62	0.4496
	69.31	30.01	70.03	30.55	69.37	30.29	68.57	29.14	68.71	28.56
S_T	30.44	0.2853	35.39	0.2818	36.06	0.2895	34.20	0.2749	34.19	0.2711
	45.47	20.16	49.30	23.97	50.38	24.64	48.18	22.97	48.4	22.90
$S_{g\backslash c}$	50.11	0.5921	50.53	0.6010	50.31	0.5990	49.62	0.5935	48.81	0.5890
	81.03	29.87	81.45	29.77	81.28	30.18	79.95	29.45	79.95	28.28

Every plan has four performance statistics under one epistemic scenario, which is shown as a two by two matrix. Expected values are in the upper left corner; standard deviations are in the upper right corner; the highest present values of profits (billion $) over 20 years are in the lower left corner; the lowest present values of profit(billion $) over 20 years are in the lower right corner. We make the following observations.

- The average performance heavily depends on the epistemic scenarios. The variation of the highest profit values among different scenario is larger than that of the lowest profit.
- The profitability of an investment plan is particularly sensitive to transmission investment. The transmission plans in S_T was especially designed to reduce system wide congestion under Plan A. As a result, the profit of Plan under S_T is much lower than other plans.
- Generally, the profits are higher under cases with carbon tax policy. Carbon tax policy adds additional cost to generation. Since the marginal generators usually have high CO_2 emissions, local marginal prices increase correspondingly. Consequently, the revenues of the generators also increase.
- Under scenario S_T, the profitabilities of all investment plans have smaller variances.

We plot the annual profit distributions of the five investment plans under four epistemic scenarios in Figures 5 to 9. We make the following observations.

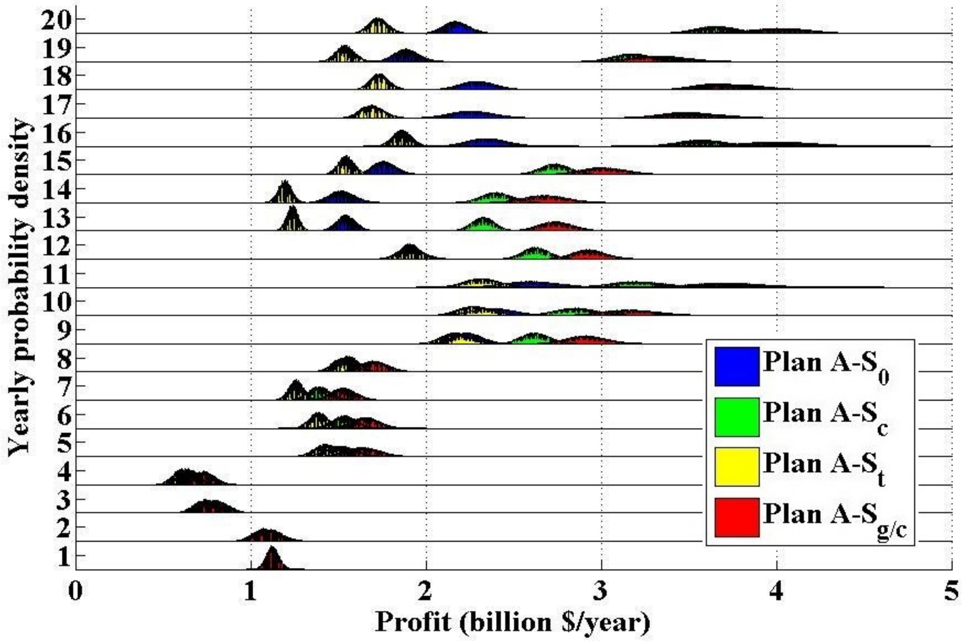

Figure 5: Annual profit distribution of Plan A

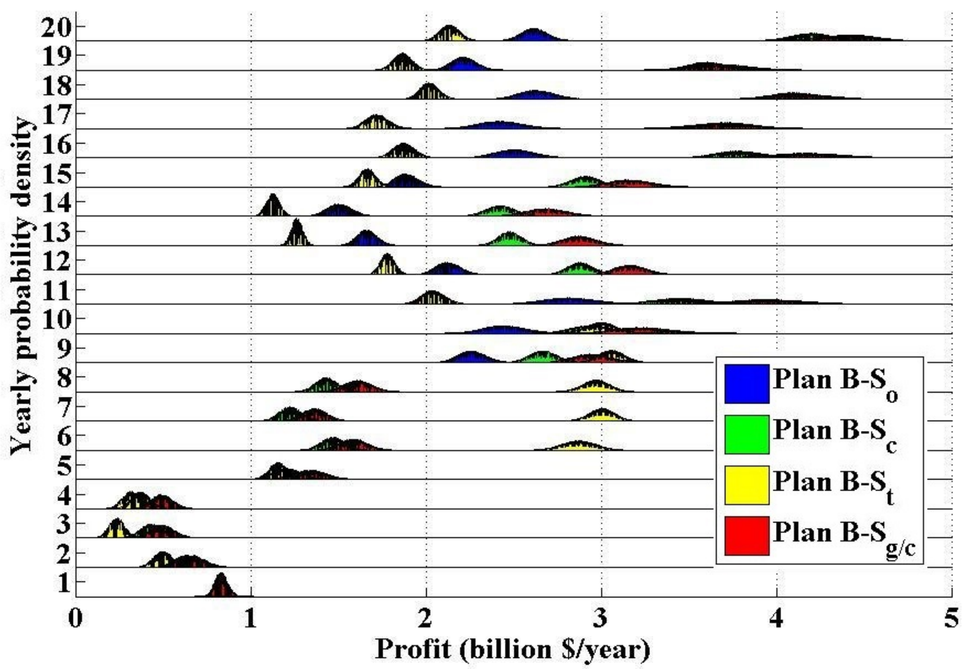

Figure 6: Annual profit distribution of Plan B

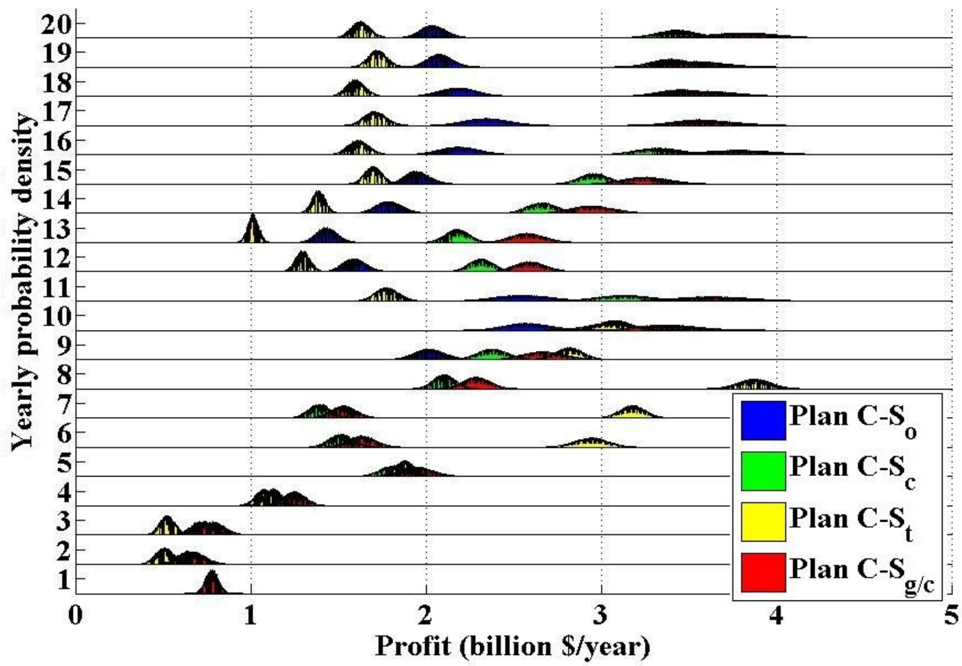

Figure 7: Annual profit distribution of Plan C

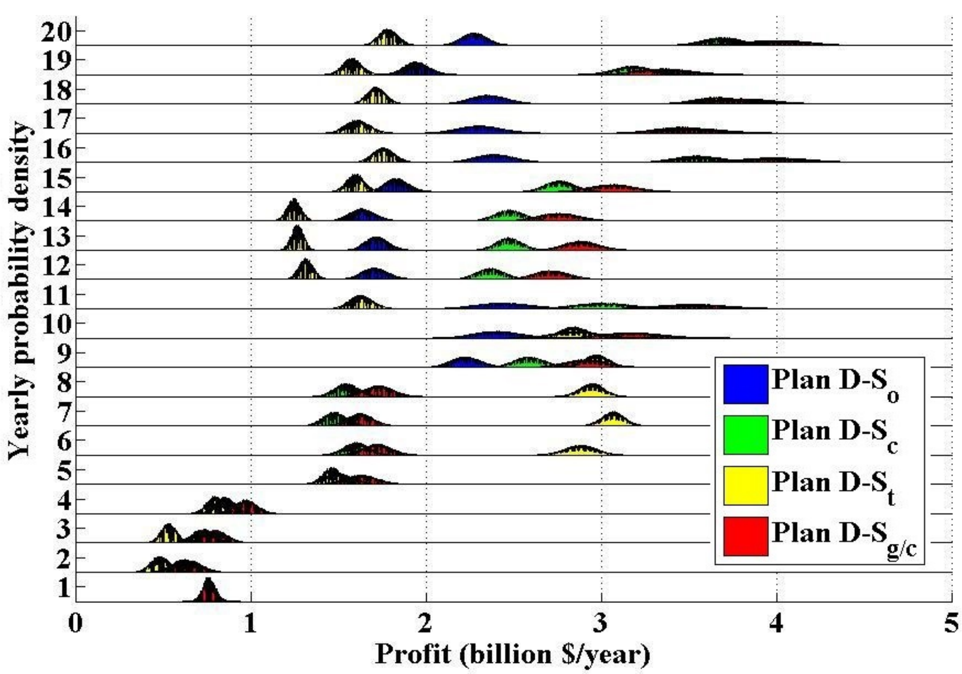

Figure 8: Annual profit distribution of Plan D

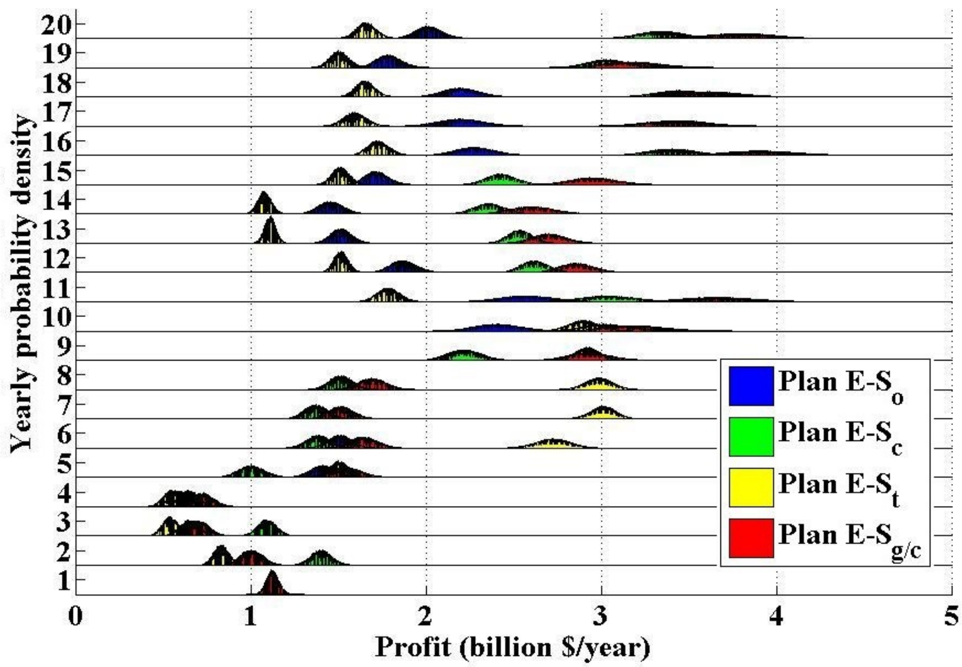

Figure 9: Annual profit distribution of Plan E

3.4.2 Annual profit distribution

Generally, the probability density functions of annual profits are bell shaped, which is because of our assumptions of aleatoric uncertainty. The density functions can not be fit as any well-known distributions. Under S_C or $S_{g\backslash c}$, the annual variances are larger than S_0 and S_T, which are consistent with the relationships of total variances. As the time goes by, there are more and more renewable generations, the variances have growing trends. At the same time, the performances are more distinguished from each others. The annual profits are winding and always positive. The annual profit performances under uncertainty could be used to improve the candidate plans. For example, a large variance is an indication of high risk in particular years.

3.4.3 Profit regrets

Tables 4 and Table 5 present the expected maximal regrets and their standard deviations of all plans under all epistemic scenarios. Figure 10 shows the cumulative density functions of the profit regrets.

Table 4: Expected maximal regrets (billion $)

	Plan A	Plan B	Plan C	Plan D	Plan E
S_0	0.3949	0.0308	0.00403	0.5128	1.475
S_C	1.0142	0	0.9239	1.8526	2.2519
S_T	7.5431	0.7883	0	2.4031	1.9149
$S_{g\backslash c}$	0.5798	0	0.4082	1.2408	1.8382

Table 5: Expected maximal regret standard deviation (million $)

	Plan A	Plan B	Plan C	Plan D	Plan E
S_0	21.68	27.55	10.71	53.09	46.71
S_C	32.40	0	0.9239	58.51	67.79
S_T	173.57	40.70	0	67.10	43.86
$S_{g\backslash c}$	42.80	0	48.10	67.56	78.00

3.4.4 Individual generator profit

We also look at individual generator profits. Some generators actually result in negative profits. The finding will help the decision maker to choose old and non-profitable generators to retire.

Tables 6 to 10 show the new generators' total profits per capacity under all plans throughout the planing horizon. In the names of the generators, the letters B, E, G, H, N, S, and W indicate the fuel type of the generator being biomass, geothermal, small hydro, nuclear, solar, and wind power plant, respectively; the number indicates the year that the generator starts its generation (treating the year 2004 as year 0). The letters after the number are the short names of generator buses. For example, generator B8FU uses biomass as the fuel, starts its generation in year 2012, and is located at bus FULTON. The generator names in Plan A are exactly the same in Plan B, but their capacities are different. The names are not unique in Plan C.

3.4.5 Emissions

Table 11 shows the expected total system's emissions of all plans under four epistemic scenarios. "Average" is with respect to the aleatoric uncertainty.

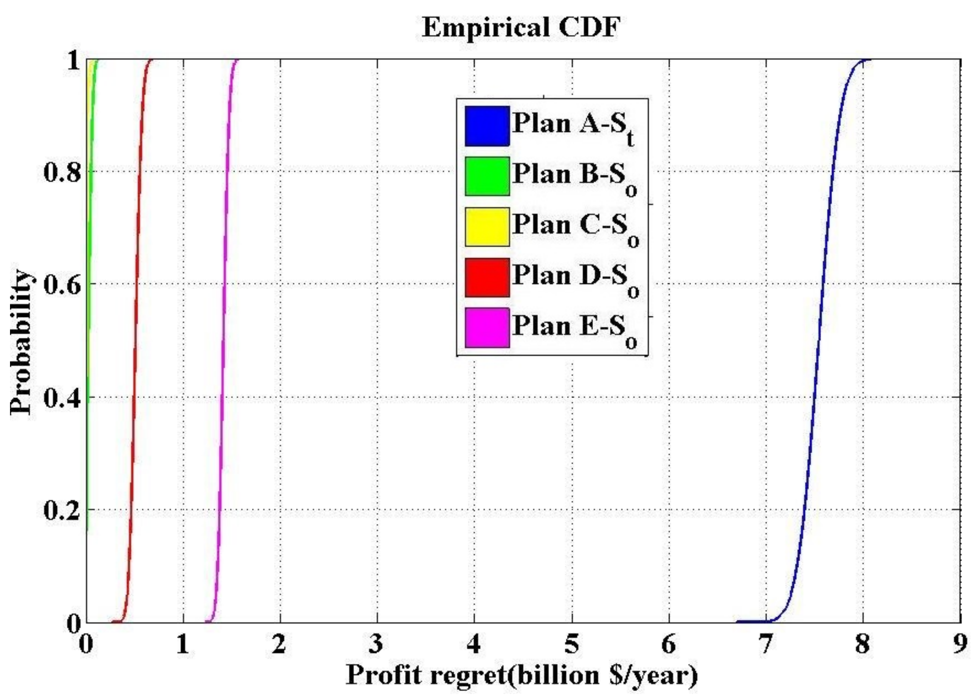

Figure 10: Profit regret cumulative density in worst epistemic scenario

Table 6: Individual new generator profits per capacity of Plan A ($M)

Generator	S_0	S_C	S_T	$S_{g\backslash c}$	Generator	S_0	S_C	S_T	$S_{g\backslash c}$
B8FU	3.27	6.10	2.59	6.42	B5PI	1.81	3.84	1.34	4.13
E5FU	6.47	8.75	5.93	9.00	B19PI	1.18	2.21	1.17	2.22
G17FU	2.52	4.59	2.07	4.58	G12PI	2.71	4.76	2.11	5.18
W3TE	0.23	0.06	0.17	0.55	B5HU	1.25	3.02	0.84	3.42
D19TE	0.89	1.70	0.85	1.85	D7HU	–0.29	–0.29	–0.29	–0.28
D8TE	2.77	4.18	2.04	4.91	D14HU	3.30	5.80	2.49	6.29
B2TE	–0.06	1.17	–0.37	1.41	B15HU	3.49	6.35	2.89	6.52
E11TE	8.81	12.50	8.29	12.39	B3SM	0.93	2.60	0.50	2.92
G4TE	1.49	2.07	1.03	2.62	B8SM	3.23	6.06	2.60	6.39
D10MC	2.98	4.92	2.18	5.80	B6SM	2.33	4.62	1.80	4.96
G15MC	3.53	6.23	2.63	6.71	D1PO	0.97	1.12	0.72	1.53
B6MC	2.41	4.81	1.88	5.39	D9PO	2.84	4.48	2.09	5.23
D19MC	1.09	2.05	0.84	2.28	G6PO	1.85	2.77	1.37	3.40
G5MID	1.91	2.80	1.49	3.89	G12PO	2.76	4.86	2.02	5.31
D10MID	3.17	5.40	2.22	6.97	D8ME	2.35	3.90	1.72	4.99
G15MID	3.80	6.72	2.33	8.18	S4ME	2.15	3.16	1.91	3.32
B3MID	1.35	3.24	0.89	4.15	S14ME	3.97	5.77	3.30	5.98
B6RO	1.38	3.19	0.70	3.30	W5ME	2.40	3.34	2.11	3.59
G8RO	2.58	4.02	1.59	4.64	W15ME	3.23	4.65	2.49	4.82
E7RO	7.62	10.35	6.52	9.94	W10ME	3.42	4.87	2.91	5.18
B14RO	3.34	6.08	2.39	5.58	W19ME	1.04	1.56	0.74	1.58
H13SU	5.07	7.32	4.39	7.05	G1SM	0.89	1.10	0.60	1.52
H3SU	3.18	4.27	2.83	4.37	G4SM	1.49	2.07	1.06	2.62
W2PI	1.09	1.66	0.97	1.71	G8SM	2.44	3.81	1.81	4.45
W8PI	2.56	3.61	2.35	3.64	G12SM	2.76	4.84	2.06	5.26
W17PI	1.89	2.84	1.83	2.67	B12SM	3.98	7.40	3.32	7.51

Table 7: Individual new generator per capacity profits of Plan B ($M)

Generator	S_0	S_C	S_T	$S_{g\backslash c}$	Generator	S_0	S_C	S_T	$S_{g\backslash c}$
B8FU	3.26	6.07	3.28	6.40	B5PI	1.80	3.81	2.58	4.11
E5FU	6.46	8.72	8.46	8.97	B19PI	1.17	2.18	1.16	2.19
G17FU	2.49	4.54	2.06	4.55	G12PI	2.72	4.74	2.12	5.18
W3TE	0.21	0.57	–0.17	0.53	B5HU	1.26	3.02	2.25	3.43
D19TE	0.88	1.67	0.84	1.82	D7HU	–0.29	–0.29	–0.29	–0.27
D8TE	2.76	4.16	1.41	4.88	D14HU	3.31	5.80	2.47	6.32
B2TE	–0.06	1.15	–1.07	1.40	B15HU	3.48	6.32	2.85	6.51
E11TE	8.78	12.44	8.17	12.31	B3SM	0.93	2.59	2.30	2.91
G4TE	1.49	2.07	0.06	2.62	B8SM	3.23	6.03	3.10	6.36
D10MC	3.02	4.97	2.03	5.88	B6SM	2.33	4.60	3.35	4.94
G15MC	3.55	6.23	2.58	6.75	D1PO	0.99	1.13	1.68	1.55
B6MC	2.43	4.83	3.83	5.41	D9PO	2.86	4.50	2.18	5.26
D19MC	1.08	2.02	0.85	2.27	G6PO	1.87	2.79	2.35	3.42
G5MID	1.99	2.90	2.85	4.02	G12PO	2.78	4.88	2.02	5.34
D10MID	3.28	5.53	1.86	7.15	D8ME	2.43	3.99	1.29	5.11
G15MID	3.86	6.80	2.31	8.32	S4ME	2.16	3.16	1.65	3.33
B3MID	1.41	3.31	1.77	4.24	S14ME	3.96	5.75	3.10	5.96
B6RO	1.34	3.12	0.21	3.25	W5ME	2.36	3.28	1.93	3.50
G8RO	2.55	3.96	0.91	4.59	W15ME	3.16	4.50	2.20	4.61
E7RO	7.55	10.24	5.73	9.83	W10ME	3.37	4.77	2.54	5.04
B14RO	3.31	6.02	2.29	5.53	W19ME	0.98	1.44	0.66	1.40
H13SU	5.07	7.31	4.36	7.05	G1SM	0.90	1.11	2.10	1.54
H3SU	3.19	4.27	2.95	4.37	G4SM	1.51	2.08	3.02	2.64
W2PI	1.09	1.65	1.39	1.70	G8SM	2.45	3.81	2.32	4.45
W8PI	2.54	3.59	2.42	3.62	G12SM	2.77	4.84	2.08	5.28
W17PI	1.87	2.81	1.81	2.64	B12SM	3.98	7.38	3.33	7.50

Table 8: Individual new generator per capacity profits of Plan C ($M)

Generator	S_0	S_C	S_T	$S_{g\backslash c}$	Generator	S_0	S_C	S_T	$S_{g\backslash c}$
B7FU	2.88	5.45	3.44	5.79	B4PI	1.41	3.24	2.19	3.54
E4FU	5.90	7.97	7.86	8.22	B18PI	2.15	4.01	2.11	3.83
G16FU	3.20	5.65	2.46	5.58	G11PI	2.65	4.57	1.96	5.07
W2TE	0.00	0.33	–0.33	0.30	B4HU	0.87	2.47	1.83	2.86
D18TE	1.63	3.07	1.53	3.13	D6HU	–0.33	–0.33	–0.33	–0.32
D7TE	2.57	3.73	1.07	4.47	D13HU	3.29	5.74	2.38	6.34
B1TE	–0.51	0.60	–1.38	0.83	B14HU	3.59	6.58	2.93	6.84
E10TE	9.01	12.57	8.13	12.63	B2SM	0.43	1.94	1.58	2.25
G3TE	1.28	1.72	0.12	2.25	B7SM	2.86	5.41	3.18	5.77
D9MC	2.95	4.67	2.48	5.59	B5SM	1.88	3.96	3.16	4.30
G14MC	3.63	6.37	2.65	6.97	D0PO	0.83	0.91	1.40	1.27
B5MC	1.99	4.17	3.69	4.73	D8PO	2.73	4.15	2.25	4.94
D18MC	1.90	3.54	1.51	3.84	G5PO	1.63	2.37	2.25	2.98
G4MID	1.77	2.48	2.33	3.47	G11PO	2.67	4.64	1.88	5.17
D9MID	2.99	4.98	2.09	6.52	D7ME	2.11	3.38	1.24	4.43
G14MID	3.93	6.93	2.37	8.42	S3ME	1.68	2.60	1.28	2.76
B2MID	0.82	2.54	0.99	3.38	S13ME	4.26	6.14	3.34	6.39
B5RO	0.89	2.52	–0.18	2.66	W4ME	2.12	2.98	1.78	3.21
G7RO	2.33	3.52	0.75	4.19	W14ME	3.45	4.95	2.60	5.15
E6RO	6.87	9.34	5.17	8.99	W9ME	3.27	4.65	2.62	4.96
B13RO	3.27	6.02	2.21	5.65	W18ME	1.85	2.73	1.34	2.82
H12SU	5.16	7.39	4.42	7.24	G0SM	0.69	0.82	1.68	1.19
H2SU	2.79	3.78	2.55	3.88	G3SM	1.28	1.72	2.59	2.25
W1PI	0.81	1.32	1.05	1.37	G7SM	2.24	3.37	2.57	4.02
W7PI	2.38	3.33	2.36	3.38	G11SM	2.68	4.63	1.94	5.12
W16PI	2.37	3.51	2.20	3.28	B11SM	3.84	7.19	3.13	7.38

Table 9: Individual new generator per capacity profits of Plan D ($M)

Generator	S_0	S_C	S_T	$S_{g\backslash c}$	Generator	S_0	S_C	S_T	$S_{g\backslash c}$
W8TE	1.17	1.78	0.91	1.70	W5ME	2.28	3.16	1.90	3.36
W5TE	0.64	1.08	0.18	1.03	W19ME	0.97	1.42	0.67	1.38
G17FU	2.65	4.77	2.13	4.82	G12PI	3.01	5.15	2.21	5.65
W3TE	0.23	0.59	–0.20	0.56	W5ME	2.28	3.16	1.90	3.36
D19TE	0.95	1.78	0.88	1.96	D7HU	–0.29	–0.29	–0.29	–0.26
D8TE	3.25	4.75	1.48	5.60	D14HU	3.49	6.03	2.57	6.59
W2TE	0.01	0.34	–0.37	0.31	W15ME	3.09	4.38	2.20	4.46
W11TE	1.41	2.11	1.33	1.98	W3ME	1.73	2.44	1.42	2.61
G4TE	1.81	2.44	0.10	3.06	W8ME	2.94	4.12	2.39	4.37
D10MC	3.23	5.20	2.11	6.17	W6ME	2.53	3.50	2.11	3.73
G15MC	3.68	6.39	2.67	6.92	D1PO	1.15	1.31	1.79	1.77
W6TE	0.83	1.32	0.44	1.27	D9PO	3.21	4.91	2.29	5.76
D19MC	1.10	2.05	0.88	2.30	G6PO	2.16	3.11	2.52	3.82
G5MID	1.89	2.73	3.03	3.82	G12PO	2.99	5.15	2.10	5.66
D10MID	3.13	5.26	1.87	6.83	D8ME	2.29	3.77	1.32	4.86
G15MID	3.71	6.54	2.34	7.98	W4ME	2.02	2.81	1.68	3.00
W3TE	0.23	0.59	–0.20	0.56	W14ME	3.30	4.67	2.39	4.76
W6TE	0.83	1.32	0.44	1.27	W5ME	2.28	3.16	1.90	3.36
G8RO	3.04	4.57	1.05	5.30	W15ME	3.09	4.38	2.20	4.46
W7TE	1.02	1.56	0.69	1.50	W10ME	3.30	4.64	2.53	4.88
W14PI	2.87	4.19	2.64	4.08	W19ME	0.97	1.42	0.67	1.38
W13PI	2.90	4.23	2.68	4.16	G1SM	1.09	1.32	2.22	1.80
W3TE	0.23	0.59	–0.20	0.56	G4SM	1.79	2.40	3.20	3.03
W2PI	1.20	1.78	1.44	1.85	G8SM	2.83	4.26	2.46	5.00
W8PI	2.72	3.80	2.47	3.88	G12SM	3.02	5.17	2.16	5.67
W17PI	1.95	2.92	1.84	2.76	W12PI	2.91	4.21	2.65	4.18

Table 10: Individual new generator per capacity profits of Plan E ($M)

Generator	S_0	S_C	S_T	$S_{g\backslash c}$	Generator	S_0	S_C	S_T	$S_{g\backslash c}$
B8TE	2.59	4.91	1.46	5.15	B5TE	1.30	3.00	–0.14	3.25
E5TE	6.79	9.11	4.28	9.24	B19TE	0.95	1.80	0.95	1.80
G17TE	2.38	4.36	2.08	4.26	G12TE	2.76	4.81	2.13	5.25
W3TE	0.22	0.58	–0.17	0.54	B5SM	1.93	4.01	3.31	4.33
D19FU	0.96	1.83	0.83	1.97	D7SM	–0.29	–0.29	–0.29	–0.26
D8FU	2.91	4.34	2.77	5.08	D14SM	3.32	5.80	2.54	6.06
B2FU	0.48	1.99	2.03	2.28	B15SM	4.20	7.57	3.51	7.37
E11FU	8.66	12.00	7.88	12.43	B3SM	1.02	2.70	2.36	3.02
G4FU	1.57	2.17	3.51	2.71	B8SM	3.34	6.19	3.08	6.50
D10HU	2.90	4.80	1.88	5.59	B6SM	2.42	4.73	3.38	5.05
G15HU	3.43	6.06	2.52	6.39	D1PO	1.02	1.18	1.67	1.59
B6HU	1.71	3.69	2.37	4.10	D9PO	2.92	4.58	2.12	5.32
D19HU	1.03	1.95	0.83	2.15	G6PO	1.93	2.86	2.33	3.49
G5MID	1.88	2.76	2.69	3.85	G12PO	2.79	4.90	1.99	5.34
D10MID	3.18	5.44	1.73	7.01	D8ME	2.34	3.90	1.35	5.02
G15MID	3.88	6.90	2.26	8.38	S4ME	2.14	3.16	1.74	3.33
B3MID	1.33	3.23	1.65	4.14	S14ME	3.99	5.81	3.26	6.05
B6RO	1.45	3.26	0.21	3.39	W5PI	1.91	2.69	2.22	2.73
G8RO	2.69	4.15	0.89	4.79	W15PI	2.63	3.87	2.44	3.69
E7RO	7.71	10.00	5.75	10.04	W10PI	2.79	3.98	2.50	3.99
B14RO	3.33	6.05	2.28	5.57	W19PI	0.73	1.12	0.74	1.11
H13SU	5.08	7.34	4.37	7.11	G1MC	0.78	0.98	2.43	1.45
H3SU	3.21	4.30	2.95	4.42	G4MC	1.46	2.04	3.48	2.69
W2TE	0.00	0.32	–0.34	0.29	G8MC	2.39	3.81	2.48	4.60
W8TE	1.15	1.75	0.94	1.67	G12MC	2.87	5.05	2.01	5.70
W17TE	1.02	1.52	1.03	1.35	B12MC	4.16	7.75	3.26	8.27

Table 11: The expected total system's emissions (million ton)

	Plan A	Plan B	Plan C	Plan D	Plan E
S_0	193.45	149.58	201.84	195.69	197.81
S_C	195.29	150.34	203.60	197.65	199.37
S_T	178.71	140.47	187.69	182.11	181.32
$S_{g\backslash c}$	198.74	155.11	207.91	200.94	205.16

3.4.6 Renewable generation portfolio

Table 12 shows iGENCO renewable generation portfolio under twenty cases, which is average renewable generation divided by average total generation.

Table 12: iGENCO renewable generation portfolio (%)

	Plan A	Plan B	Plan C	Plan D	Plan E
S_0	30.82	40.97	31.09	29.28	29.45
S_C	31.15	41.23	31.43	29.56	29.79
S_T	31.34	41.13	31.24	29.20	29.43
$S_{g\backslash c}$	30.94	40.95	31.18	29.58	29.42

3.4.7 Expected total system's profit and profit difference

Table 13 shows expected total system's profits of all plans under four epistemic scenarios. "Average" is with respect to the aleatoric uncertainty. A "case" is defined as one plan under an epistemic scenario. Table 14 shows the revenue differences with respect to Plan A under very epistemic scenarios from iGENCO and non iGENCO entities. The last row is the investment cost difference.

Table 13: Expected total system's profit (billion $)

	Plan A	Plan B	Plan C	Plan D	Plan E
S_0	350.54	351.43	351.95	363.77	352.38
S_C	491.50	492.74	493.21	505.13	493.56
S_T	334.96	341.58	340.63	345.44	340.37
$S_{g\backslash c}$	547.57	548.54	550.46	565.54	550.20

3.4.8 Curtailment

Table 15 shows expected total system's curtailment of all plans under four epistemic scenarios. "Average" is with respect to the aleatoric uncertainty. The curtailment is less than 5% in any hour during the whole planning horizon.

3.4.9 Result summary

The plans are designed to answer questions on locations, timing, technologies, capacities of investment. Plan A is a moderate baseline plan. Plan B increases the investment in renewable generation, significantly reduces the emissions and increases the renewable energy portfolios. However, the variances do not significantly increase in Plan B. It is because the options of renewable generators. A lot of stable generators like

Table 14: Expected tota system's profit difference (billion $)

	Plan A	Plan B	Plan C	Plan D	Plan E
S_0 iGENCO	0	4.0169 (0.26)	0.2119 (0.41)	0.8565 (–0.09)	–1.01 (–1.01)
S_0 non iGENCO	0	0.63	1.00	12.373	2.85
S_C iGENCO	0	4.6769 (0.92)	–0.0781 (0.12)	0.2465 (–0.7)	–1.26 (–1.26)
S_C non iGENCO	0	0.32	1.59	14.33	3.32
S_T iGENCO	0	8.7069 (4.95)	5.4219 (5.62)	4.7065 (3.76)	3.75 (3.75)
S_T non iGENCO	0	1.67	0.05	6.72	1.66
$S_{g\backslash c}$ iGENCO	0	4.1769 (0.42)	0.0019 (0.2)	0.4565 (–0.49)	–1.3 (–1.3)
$S_{g\backslash c}$ non iGENCO	0	0.55	2.69	18.4	3.93
Investment Cost	0	3.97569	–0.1981	0.9465	0

Table 15: Expected total system's curtailment (million MWh)

	Plan A	Plan B	Plan C	Plan D	Plan E
S_0	8.7437	8.8711	8.5069	9.6178	8.8281
S_C	8.8054	8.9338	8.5774	9.6943	9.2048
S_T	7.7196	22.306	20.595	23.888	22.014
$S_{g\backslash c}$	11.579	11.779	11.397	13.094	11.742

geothermal, small hydro and biomass generators are considered. Plan C makes all generator invested in one year earlier. It increased the CO_2 emissions due to early depreciations of generators. It increased the renewable generation portfolio, since there is less competition of renewable energy if the renewable generators are invested earlier. Plan D studies portfolio of generators. Wind energy is not fully delivered to the grid and results in less renewable energy portfolio and more emissions, compared to Plan A. Plan E switches the generators to nonprofitable locations and reduces the profits.

The performances of individual generation companies do not necessarily have positive correlation with the corresponding performance of the whole systems. For example, Plan D outperforms other plans in all epistemic scenarios with respect to the total system's profits, while it does not with respect to iGENCO profits. Profits per capacity could be a useful indicator to determine the expansion, retrofit, retirement or deferring investment of individual generators. The performances of all plans are similar in different epistemic scenarios.

4 Conclusion

Investment in new generation capacity is critical to maintain the power system's capability to provide reliable and economic electricity to meet the growing demand. For individual generation companies, correctly-timed investment into the appropriate generation technology located at the appropriate site will yield a future stream of beneficial returns over many years to come. Conversely, a misguided investment could lead to unforeseeable and undesirable consequences that not only negatively impact the profitability of the company but also may compromise the reliability of the power system. The pursuit of an effective strategy to formulate profitable investment plans has been one of long interest, yet many existing strategies have limited capability to address some significant challenges. A particularly good example is the inability of many current approaches to explicitly consider the compliance requirements imposed by various environmental policy legislative and regulatory initiatives so as to reduce the environmental impacts of electricity operations. Moreover, uncertainty on both demand side – short-term load variations and long-term growth patterns – and supply side due to the deeper penetration of the variable and intermittent outputs of renewable energy resources introduces major complications in the quantitative measure of the risk and return associated with the investment. The additional sources of uncertainty in the competitive environment further complicate the analysis due to the interactions of the independent decisions of the various market participants and their impacts on grid congestion and the outcomes of transmission constrained electricity market. The objective of this project is to effectively address the many complicating factors in the investment decision-making area with the explicit consideration of the impacts of environmental regulations and of key sources of uncertainty. To meet this objective, we constructed an appropriate analytical framework to facilitate the analysis of the issues so as to lead to the selection of improved investment decisions.

The proposed analytic framework provides the capability to assess the profitability of the investment decision over a longer period by taking into account the ramifications under the considered sources of uncertainty and directly incorporating the compliance requirements of environmental restrictions. The framework makes detailed use of probabilistic and scenario analysis so as to quantify the uncertain outcomes. For example, the methodology can quantify the returns on an investment in intermittent wind generation turbines as well as those on a coal-fired generation unit investment under the various environmental restrictions that impact its operations. Furthermore, the framework is effective in the analysis of *what if* questions to study the impacts of a large number of issues, such as various transmission expansion alternatives, implementation of significant wind generation projects by a competitor generation company, and termination of production tax credits for renewable energy generation.

The modeling framework has a three-layer structure. The decision maker interfaces with the optimization layer through the input of a set of candidate investment plans. The information flow among the three layers allows the comparison of the various alternatives on a consistent basis in line with the decision maker's preferred tradeoff criteria between risk and return in terms of expected value, or worst scenario or maximal regret. The assessment layer analyzes comprehensively each investment plan under the represented sources of uncertainty. The computational engine in the operations and market layer simulates the clearing of the hourly transmission-constrained markets by solving the DCOPF formulation for the market clearing problem. In this way, the analysis explicitly accounts for temporal and spatial correlation among the loads and renewable resource outputs under transmission network constraints. Also, the analysis considers the impacts of the retirement of generation capacity, addition of new capacity, transmission expansion, and load growth. Indeed, the framework allows the ranking of the various alternatives in terms of specified metrics on a meaningful basis. The framework is a practical decision tool to help both planners and investment analysts to make better-informed decisions by explicitly taking into account various sources of uncertainty and the requirements of compliance with environmental regulations.

We illustrate the application of the framework with numerical results from representative case studies carried out on the 240-bus WECC test system. Our studies indicate the effectiveness of the analysis of the decision alternatives by the three-layer framework so as to effectively construct an investment plan in line with the decision maker's preferences. The studies show the sensitivity of alternatives to the technology type, implementation timing, siting location, and generation capacity addition. Results using the proposed framework, with proper visualization, reveal insights into the consequences of an investment plan that could not have been available without the framework. This project produces a set of practically oriented results of direct benefit to decision makers, who can gain insights into the planning strategies and investment decisions from framework that involves multiple market players and entities, each making investment decisions with the explicit consideration of compliance with the environmental regulations. The case study results are particularly useful to understand the impacts of each individual investment company's strategy on the power system's overall generation adequacy in meeting the forecasted loads and in the resulting market performance. The report discusses in detail the analytical basis for the framework, analyzes the case study results and provides an interpretation of the ramifications of investment decisions made with the developed framework.

5 Future work

Future research on related topics should build upon our new framework and focus on addressing its limitations. The framework has two major limitations. First, it requires significant computational resources, both in terms of computational time and hardware/software requirements. This is because probabilistic and scenario analysis requires extensive computation to examine a realistic-sized 240-bus WECC test system at a granularity of an hourly market clearing level for a 20-year planning horizon. To address this difficulty, a compromise on the modeling resolution appears to be inevitable. The second limitation is the lack of a capability to generate the optimal investment plan. This is due to the extremely complex nature of the problem. If manually generated candidate investment plans is unavailable, then one should further simplify the modeling framework in order to construct a computationally tractable model to compute for an optimal solution under a given set of criteria.

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Appendix A: Notation

Sets:

$\mathscr{I}$	set of nodes (buses), $i, j \in \mathscr{I}$
$\mathscr{M}$	set of generation companies, $m \in \mathscr{M}$
$\mathscr{G}$	set of types of generation technologies, $g \in \mathscr{G}$
$\mathscr{G}^{\mathrm{s}}$	set of types of storage technologies, $g^{\mathrm{s}} \in \mathscr{G}^s$
$\mathscr{G}^1$	set of renewable generation technologies, $g^1 \in \mathscr{G}^1$.
$\mathscr{G}^2$	set of nonrenewable generation technologies, $g^2 \in \mathscr{G}^2$
$\mathscr{L}$	set of transmission lines, $l \in \mathscr{L}$. $l(o,i,j)$ contains line's "from" node i,"to" node j information and identification number o for overlapped lines.
$\mathscr{L}^1$	set of transmission lines to be constructed, $l^1 \in \mathscr{L}$
$\mathscr{H}$	set of hours, $h \in \mathscr{H}$
$\mathscr{Y}$	set of years, $y \in \mathscr{Y}$
$\mathscr{T}$	set of weeks $t \in \mathscr{T}$

Parameters:

Q_{ihy}	electricity demand at node i at hour h, in period y. (MW)
γ_l	susceptance of line l. (S)
F_l	transmission capacity of line l. (MW)
η_{mighy}	capacity factor of technology g owned by generation company m at node i in period y. η_g is short for η_{mighy}. (unitless)
$\varsigma_{mig^{\mathrm{s}}y}$	charging/discharging efficiency of technology g^{s} owned by generation company m at node i in period y. (unitless)
G_{migy}	capacity of technology g owned by generation company m at node i in period y. (MW)
E_{migy}	emission rate of technology g owned by generation company m at node i in period y. (ton/MWh)
A_y	emissions cap under cap-and-trade policy in period y. (ton)
I^{G}_{igy}	investment cost of technology g at node i in period y. (\$/MW)
C_{migy}	operations cost of technology g owned by generation company m at node i in period y. (\$/MWh)
V_{ihy}	electric vehicle demand at node i at hour h in period y. (MW)
C^{t}_{igy}	tax (carbon price)(positive) or subsidy (negative) of technology g at node i in period y. (\$/ton)
$S^{\min}_{mig^{\mathrm{s}}y}$	minimal state of technology g^{s} owned by generation company m at node i in period y. (MWh)
$S^{\max}_{mig^{\mathrm{s}}y}$	maximal state of technology g^{s} owned by generation company m at node i in period y. (MWh)
$DSM_{i,y}$	load ratio that is subject to demand side management at node i in period y. (unitless)
a^{G}_{migy}	service status of generator g owned by generation company m at node i. If a^{G}_{migy} =1, the generator is in service. (unitless)
a^{L}_{ly}	service status of transmission line l in period y. If a^{L}_{ly} =1, the transmission line is in service. (unitless)

n^{L}_{ly}	transmission expansion decision binary variable, element is n^{L}_{ly}, if n^{L}_{ly} =1, Line l would be in service in year y. We assume n^{L}_{ly} =1 for existing transmission lines, and n^{L}_{ly} =0 for retired transmission lines. (unitless)
n^{G}_{migy}	generation expansion decision binary variable, if n^{G}_{migy} =1, generator of technology g located at node i would be expanded by generation company m and in service in year y. We assume n^{G}_{migy} =1 for existing generators, and n^{G}_{migy} =0 for retired generators. (unitless)
$C^{\mathrm{s}}_{mig^{\mathrm{s}}y}$	storage operating cost of technology gs owned by generation company m at node i in period y. (\$/MWh)
Ω	payment for per MWh not-served load. (\$/MWh)
S_{liy}	node-arc incident element in period y. (unitless)
N_t	maximal number of generators under maintenance in week t. (unitless)
x_{gt}	maintenance status for generator g at time interval t. (unitless)
D^T_g	total maintenance time for generator g during the planning horizon. (week)
D_g	time duration of one maintenance for generator g during the planning horizon. (week)
S_g	minimal maintenance time separation of generator g. (week)

Decision variables:

q^{s}_{mighy}	electricity supply by generation company m at node i at hour h in period y by technology g. (MW)
q^{d}_{ihy}	real electricity demand at node i of technology g at hour h in period y. (MW)
f_{lhy}	power flow in line l at hour h in year y. (MW)
θ_{ihy}	voltage angle of node i at hour h in period y. (radius)
$s^{\mathrm{c}}_{mig^{\mathrm{s}}hy}$	storage charging quantity of technology g^{s} owned by generation company m at node i at hour h in period y.s^{c}_h is short for $s^{\mathrm{c}}_{mig^{\mathrm{s}}hy}$. (MWh)
$s^{\mathrm{d}}_{mig^{\mathrm{s}}hy}$	storage discharging quantity of technology g^{s} owned by generation company m at node i at hour h in period y.s^{d}_h is short for $s^{\mathrm{d}}_{mig^{\mathrm{s}}hy}$. (MWh)
$\mathrm{S}_{mig^{\mathrm{s}}hy}$	storage state of technology g^{s} owned by generation company m at node i at hour h in period y. (MWh)
q^{fix}_{ihy}	fixed demand at node i at hour h in year y. (MW)
q^{flx}_{ihy}	flexible demand under demand side management at node i at hour h in year y. (MW)
r_{ihy}	not-served load at node i at hour h in year y. (MW)

Appendix B: Formulation of the operations and market layer

In this section, economic dispatch problem is formulated using DC power flows. For notation simplicity, we define a power flow incident matrix S_{liy}. For a transmission line $l = l(o,i,j)$, S_{liy} =-S_{ljy}=$a^{\mathrm{L}}_{ly}n^{\mathrm{L}}_{ly}$. In this way, the incident matrix would be updated under each scenario, but the dimensions are predefined and will not change. Number of rows is equal to the total number of existing and candidate transmission lines.

The detailed economic dispatch problem is formulated as in (1) to (14). Independent Systems Operator (ISO) collects the supply and demand bids from the generation companies and load serving entity (LSE), and execute the economic dispatch. We use linearly approximated power flows, and the problem is linear when the investment plans and uncertainty are known. We assume that the economic dispatch is done at a time for one period. We neglect to time the fixed time interval ($\Delta h = 1$) in this problem.

The formulation of economic dispatch in period y can be written as:

$$\min \quad \textstyle\sum_{migh}(C_{migy}+C^{\mathrm{t}}_{igy})q^{\mathrm{s}}_{mihy}+\sum_{mig^{\mathrm{s}}h}C^{\mathrm{s}}_{mig^{\mathrm{s}}y}(s^{\mathrm{c}}_{mihg^{\mathrm{s}}y}+s^{\mathrm{d}}_{mihg^{\mathrm{s}}y})+\Omega\sum_{ih}r_{ihy} \tag{1}$$

$$\text{s.t.} \quad \textstyle\sum_{mg}q^{\mathrm{s}}_{mighy}+r_{ihy}-q^{\mathrm{d}}_{ihy}-\sum_{mg^{\mathrm{s}}}(s^{\mathrm{c}}-s^{\mathrm{d}})=\sum_{l}S^{\mathrm{T}}f,\forall i,h \tag{2}$$

$$f_{lhy}=\gamma_l(\textstyle\sum_i S_{liy}\theta_{ihy}),\forall l,h\in\mathscr{L}, \tag{3}$$

$$-\pi\le\theta_{ihy}\le\pi,\forall i,h \tag{4}$$

$$-F_l\le f_{lhy}\le F,\forall l,h\in\mathscr{L}, \tag{5}$$

$$q^{\mathrm{S}}_{mighy}\le a^{\mathrm{G}}_{migy}n^{\mathrm{G}}_{mig}\eta_{mighy}G_{migy},\forall m,i,g,h \tag{6}$$

$$s_{mig^{\mathrm{s}}(h+1)y}\le s_{mig^{\mathrm{s}}hy}+\varsigma_{mg^{\mathrm{s}}i}s^{\mathrm{c}}_{mig^{\mathrm{s}}hy}-(\varsigma_{mg^{\mathrm{s}}i})^{-1}s^{\mathrm{d}}_{mig^{\mathrm{s}}hy},\forall m,i,h,g^{\mathrm{s}} \tag{7}$$

$$S^{\min}_{mig^{\mathrm{s}}}\le s_{mig^{\mathrm{s}}hy}\le S^{\max}_{mig^{\mathrm{s}}},\forall m,i,h,g^{\mathrm{s}} \tag{8}$$

$$q^{\mathrm{d}}_{ihy}=q^{fix}_{ihy}+q^{flx}_{ihy},\forall i,h \tag{9}$$

$$q^{fix}_{ihy}=(1-DSM_{ih})(Q_{ihy}+V_{ihy}),\forall i,h \tag{10}$$

$$\textstyle\sum_h q^{flx}_{ihy}=DSM_{iy}\sum_h(Q_{ihy}+V_{ihy}),\forall i \tag{11}$$

$$\textstyle\sum_{migh}E_{migy}q^{\mathrm{s}}_{mighy}\le A_y \tag{12}$$

$$q^{\mathrm{d}}_{ihy},q^{\mathrm{s}}_{mighy},s^{\mathrm{c}}_{mig^{\mathrm{s}}hy},s^{\mathrm{d}}_{mig^{\mathrm{s}}hy}\ge 0,\forall i,g,h \tag{13}$$

$$\theta_{ihy},f_{lhy}\ \text{free},\forall l,i,h \tag{14}$$

- The terms in the objective function are, respectively, operation cost and carbon tax or subsidy, storage operating cost, and load curtailment payment. The load-not-served is subject to a penalty payment. In order to compatible with fuel price growth, the penalty cost is set to be as the 1.5 times of the highest operations cost (including carbon price if there is any).

- Constraint (2): power balance between supply and demand at node i in period y. Left hand side is the net power injection at node i expressed in terms of power supply and demand at node i, and the right hand side is the net injection expressed in terms of power flows, which is Kirchhoff's Current Law. The hourly time-varying electricity demand is inelastic to the electricity price without demand side management.

- Constraint (3): power flow through line $l = (o,i,j)$, which is Kirchhoff's Voltage Law.

- Constraint (4): voltage angle constraint at node i. The voltage angle can not exceed $[-\pi,\pi]$.

- Constraint (5): transmission capacity constraint, which is given and would be fixed through the planning horizon. We do not consider the depreciation of the line capacity. S incident matrix and 3 would ensure the flow in outage line l is zero.

- Constraint (6): maximal power generation from generator (i,g). Both a^{G}_{migy} and n^{G}_{migy} has to be 1 in order to supply power, either $a^{\mathrm{G}}_{migy} = 0$ or $n^{G}_{migy} = 0$, the generator does not supply any power.
- Constraint (7): storage state at hour h, it is determined by the previous hour state and charging and discharging quantities at hour h.
- Constraint (8): maximal and minimal storage state at hour h.
- (9)-(11): The load is decomposed into flexible load q^{flx} and fixed load q^{fix} in 9. The flexible load q^{flx} is subject to demand side management in 11. 10 is the amount of hourly fixed load.
- Constraint (12): Total CO_2 emissions from the generators are subject to the cap-and-trade policy. Since the trading profit or cost of CO_2 emissions allowance are internal from the ISO's point of view, we do not consider the trading profit or cost in the objective function.
- Constraint (13) and (14) are the decision variable domain.

Equation (1) to (14)generalized to accommodate many possible modifications. In our case study, we focus on the generator technology, and do not consider the maintenance, element outages, demand side management and storages. DSM_{iy} and storage capacities are all set to be zero. The emission cap is infinity. The service status and outage status parameters are all equal to one.

Maintenance scheduling

Maintenance scheduling determines the time the generators become off-line. During the long-term planning, the maintenance scheduling is important, because generators must schedule a large portion of time on maintenance, and would not create profits during the maintenance. The profits would be different. The assessment results of the corresponding investments would deviate a lot from no maintenance case. Therefore, it is crucial to include maintenance schedule into the operations and market layer. Optimization of maintenance scheduling is a complex topic in restructured power systems. It is frequently modeled as integer problems [16, 24, 37]. In our test systems, we will have more than nine hundred generators and for long-term planning under uncertainty. It is extremely difficult to find the optimal solutions. In addition, assessment is our emphasis instead of optimal maintenance schedule, We do not optimize the maintenance scheduling under uncertainty. Our study finds that the maintenance scheduling is not important in our framework.

In the study, we generate a feasible maintenance scheduling through the planning horizon instead of an optimal one. The maintenance take weeks and can be scheduled on seasonal or annual basis. We consider schedule generator maintenance yearly. The maintenance feasible schedule is found from equation (15)-equation (18)(abstracted from [14]).

$$\sum_{t=1}^{T} x_{gt} = D_g^T \tag{15}$$

$$x_{gt} - x_{g(t-1)} \leq x_{g(t+D_g-1)} \tag{16}$$

$$\sum_{g} x_{gt} \leq N_t \tag{17}$$

$$\sum_{\tau=1}^{t} x_{g(\tau-D_g-S_g)} - x_{gt} \geq 0 \tag{18}$$

- Equation (15) is constraint on the total time required for maintenance.
- Equation(16) is maintenance time continuity.
- Equation (17) says total number of generator on maintenance during a time interval can not exceed maximal maintenance number due to crew availability or system reliability.
- Equation (18) means the minimal time length between two consecutive maintenance of a generator.

In order to simply our problem, we assume the maintenance happens and ends at the beginning and the end of a week. The maintenance durations varies among generators, but we assume they all take one week. When a candidate investment specified, a feasible maintenance schedule is obtained and passed to the operations and market layer. We called it with-maintenance case.

We also run the results without maintenance scheduling, but apply discount on the generator availability to model the maintenance effect. For example, if the generator takes n weeks to complete a scheduled maintenance in a year, we will apply $n/52$ discount on the generator availability to model the maintenance effect and keep the problem linear. We called the latter case the discounted case.

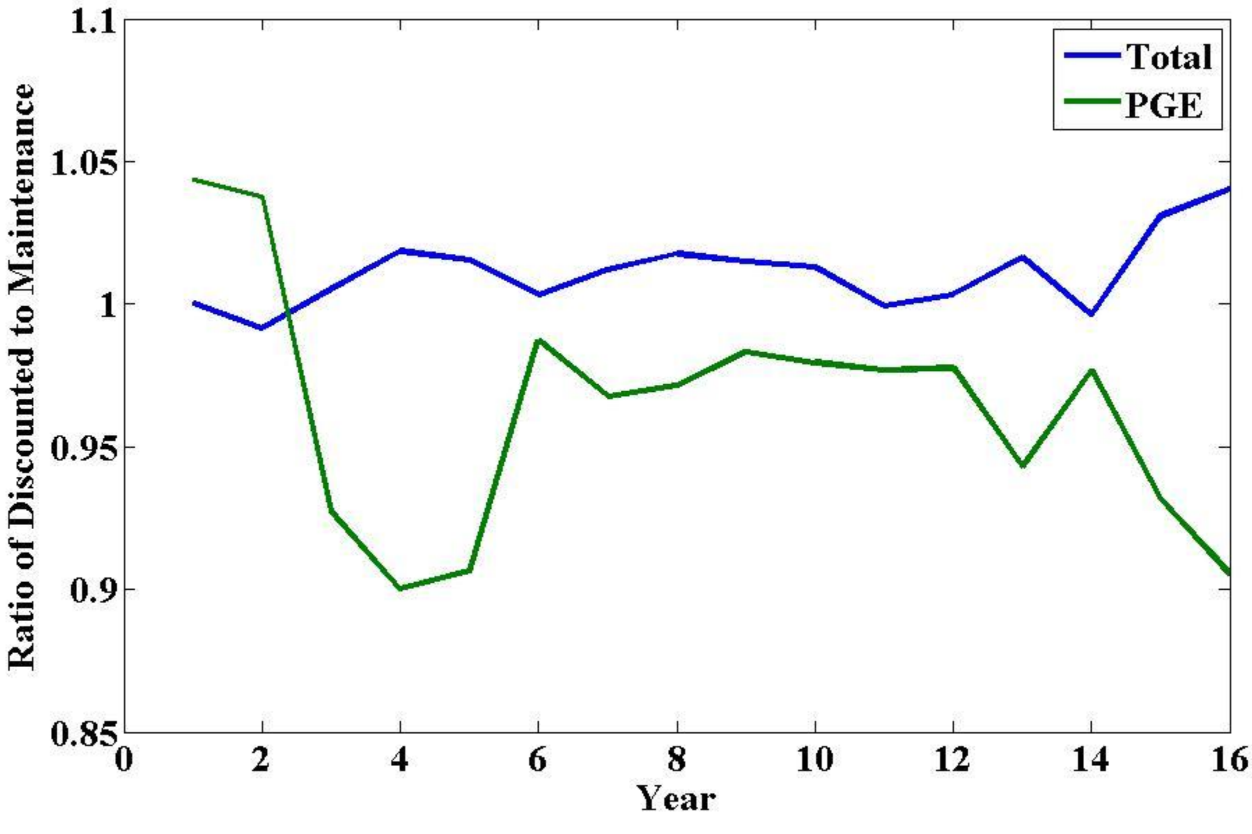

Figure 11: Ratio of the discounted case to with-maintenance case

The results shows that annual profits are almost the same in both cases for all generation companies. As shown in Figure 11, the horizontal axis is the average profit ratio of discount-maintenance test to with-maintenance test. The blue line is the ratio curve for the whole systems' profit from year 1 to year 16. The green line is the ratio curve for iGENCO's profit from year 1 to year 16. They are compared under the same epistemic scenario and investment plan. The ratio stays between 0.90 and 1.05. The total profit of the whole systems is 1.013 in discount-maintenance test than in with-maintenance test. Since profits are not significantly different in both cases, in order to simplify our problem, in the case study, we continue to apply the discount on the generator availability, instead of using a feasible maintenance plan.

Appendix C: Data in the case study

This section introduces the resource characteristics inherit from [29] and parameters used in the case study.

Resource characteristics

Existing system conditions are represented as the year 2004, and future conditions as the year 2015. The resource characteristics, which will be used in our case study, are as follows:

- Hourly time-varying load profiles for 21 areas in the whole systems are provided in 2004, as well as load of California Department of Water of Resources (DWR). It also includes the load participation factor of all buses. All the areas have exclusive buses.
- Hourly time-varying profiles for wind and solar resources are aggregated to the buses in the network for both current and future time frames. There are three aggregated wind areas and one solar area within CAISO. Meanwhile, there are thirteen aggregated wind areas and four solar areas (one in the future time frame) outside CAISO.
- Hourly time-varying profiles for geothermal and biomass resources are aggregated within CAISO. Biomass outside CAISO is aggregated into generic renewable resources. The geothermal output is assumed to be 80% of maximal capacities.
- If there is no dominant renewable resources and total capacity is limited, the renewable resources are modeled as generic renewable energy with 70% capacity factor. However, in our study, generic renewable resources are modeled as 70% of maximal capacity instead of 80%.
- Gas-fired generator is modeled as a dispatchable by using heat rate from CAISO transmission study data.
- Coal gasification-fired generator is modeled as gas-fired generation. There is no coal generator within CAISO, although CAISO might have ownership of coal-fired generators located outside CAISO.
- There are two nuclear sites within CAISO and two outside CAISO, modeled as 85% to 100% of capacity.
- Optimal scheduling or dispatch of hydroelectric generation is complex due to various water flows. The hourly time-varying profile is obtained from PLEXOS simulation.

Besides the resource characteristics listed above, the data file also includes ownership of generators within CAISO. Generators outside CAISO are aggregated to buses in both current and future time frames. The generators specifications contain ownership, capacity, heat rate, resource type, capacity factor, and location. Transmission line specifications include from-bus, to-bus, capacity and impedance (The transformer is modeled as transmission line). Generally, the transmission lines from 20kV to higher voltages are with infinite capacities; lines between higher voltages have higher capacities than lines between lower voltages. It could be multiple transmission lines connecting two buses. Generator ownership outside CAISO is modeled as “WECC” Generator ownerships within CAISO are PG&E, WESC, CDWR, NCPA, SCEC, SDG&E, PASA, MISC, SMUD, WAPA, SCEM, ECI, RESI, CPCO, TEK, CCSF, DETM, MDSC, NCVU, and SCVU. NCVU and SCVU are northern and southern California vertical utilities, and barely own generators.

Parameters

In order to accommodate the environmental study, emission rate is added to generator specifications. The emissions rate from the same type of generators is not differentiated. Renewable resources are all carbon clean. Emissions from biomass technologies are not considered as environmental polluted emissions. Similar to emission rate, fuel price are not differentiated among the same type of technologies. Heat rate for renewable technologies are all zeros. Parts of heat rates are given in the data file, and the other missing heat rates are assigned as Table 17 shows. The assigned heat rates also only depend on the types of technology. Table 17 also lists the emission rates and fuel prices of new generators.

Table 17: Emission rate, heat rate, fuel price, and overnight capital cost

Generator	Geothermal	Dual-Fuel	Gas	Biomass	Nuclear	Dist Oil	Coal
Emission rate (ton/MWh)	0	440	400	0	0	758	1020
Heat rate (MMBTU/MWh)	34.69	6.7	7.2	9.646	10.5	16.03	9.79
Fuel price ($/MMBTU)	0	4.5	4.0	1.6	0.75	13.23	1.5
Overnight capital cost (million $/MW)	3.24	5.50	7.80	2.50	2.82	1.45	1.54

In addition to the above, we have the following assumptions for the parameters:

- Transmission line capacity is constant through the planning horizon.
- Generation capacities are geometrically depreciated 5% annually.
- Generator's emission rate is geometrically depreciated 5% annually.
- Electricity demand increases linearly 1% annually.
- All fuel prices increase geometrically by 5% annually, except for coal, which increases by 10%.
- Variable O&M costs geometrically increase by 5% annually.
- Heat rates linearly increase by 5% annually.
- Capacity factor of the same type of generator is identical at the same hour in the same bus from year to year. The first year's capacity factors are derived from the given data. The hourly capacity factors of biomass, geothermal, generic renewable, hydro, wind and solar are equal to the generation output divided by 125%, 115%, 135%, 120%, 100% and 110% of the maximal output, respectively.
- Since only the aggregated generation profile is available, we assume the hourly time-varying capacity factors are the same for the same type of renewable technologies in the same buses.
- Generator capacities depreciate by 5% annually, but they do not retire completely. This assumption is made to account for the loss of generation capacity due to retirement in a gradual and even manner due to lack of information about individual firms' retirement plans.
- We assume an investment planning horizon from 2004 to 2024.

Appendix D: Assumptions for the operations and market layer

The main function of the operations and market layer is to execute market clearing and return comprehensive market outcomes under all scenarios generated in the assessment layer. In the operations and market layer, we assume all the information in the market is complete and known by the system operator. Oligopolists compete to occupy the majority of the restructured energy market. There is no entry or exit of new or existing market players. Generation companies are oligopolists in the energy market.The system operator regulates the market and is in charge of market clearing. Generation companies are profit seekers and have rational perceptions of market evolvement and development. The transmission network is regulated by the system operator as well. Generation companies do not own the transmission facilities. We do not explicitly model unit commitment of generators, but use lossless DC power flows to obtain market outcomes. The system operator clears the market in a given time interval (hourly) for all the scenarios given in the assessment layer. We assume that generation companies submit true capacities and operation costs to Independent Systems Operator (ISO) and the bidding strategies are not considered in the framework. All generation companies submit their true supply pair (price, capacity) to the system operator, where the price is operation cost (including fuel cost) and capacity is the maximal capacity times the capacity factor. Each generator can only submit one pair bid in any hour. If the investing generation company has a candidate expansion plan, it would reflect in the form of new supply pair. The transmission network, electricity demand, carbon tax, fuel prices and so on are known parameters in the operations and market layer. The transmission network and generator portfolio are subject to transmission and generation expansion decisions. We do not model fuel transportation or generator outages. The fuel resources are infinite in the formulation.

Appendix E: Assumptions for the assessment layer

Assumptions on generation expansion alternatives

- The generator capacity must be an integer number, since the results are in sensitive to small modifications of investments.
- New generators can only be installed in existing generator buses (buses of existing generators). Buses with generators in the future time frame could also be viewed as generator buses.
- Candidate generators could be small hydro ($\leq$ 30MW), nuclear, wind, solar, geothermal, dual-fuel, gas, biomass, distilled oil or coal generators.
- The investments of the same types of small generators in the same year are aggregated into one big generators of the same type in the same year.
- Generation companies are not responsible for penalty payment of not-served loads.
- The generator investment cost is equally distributed through the construction time. The investment decisions include generator types, capacities, locations and starting times. Other information such as emission rate, construction lead time, variable O&M cost and capacity factor are determined by the generator type and location.
- Interest rate is 5%. (Note that more recent weighted average cost of capital is close to 10%, which may be a more realistic assumption than the 5% used in our case study).
- Renewable generations include generations from small hydro ($\leq$ 30MW), biomass, geothermal, wind, solar generators.
- Generation growth rates of all generation companies are consistent with the load growth rate. The generation shares of generation companies are not changed significantly. We do not consider speculators in the market.
- The compliance of RPS is not mandatory. Generation companies invest towards the goal of RPS voluntarily. The compliance is not guaranteed, but the realization would not be far away from the goal.

Assumptions on transmission expansion alternatives

- New transmission lines can be invested on existing routes or new routes satisfying rules below.
- New transmission lines rarely cross long physical horizon, unless there are existing route. Most candidate line investments are within areas, a few of them are inter-area.
- New lines can be invested between the same voltages or 230KV to 115KV, 230KV,345KV and 500KV, and 345KV to 500KV.
- The technology parameters like impedance and capacity use the existing technology data. For example, system operator plans to build new line between Bus A and Bus B, they are both 230 KV. Then it should look for all the existing lines with both ends of 230 KV, and use one technology of them as new line technology.
- We do not consider the transmission expansion costs in the analysis.