ABSTRACT

Title of Document: OFFTAKE STRATEGY DESIGN FOR WIND ENERGY PROJECTS UNDER UNCERTAINTY

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Energy use from wind, solar, and other renewable sources is a public policy at the federal and state levels to address environment, energy, and sustainability concerns. As the cost of renewable energy is still relatively high compared to fossil fuels, it remains a critical challenge to make renewable energy cost competitive, without relying on public subsidies. During recent years, much advance has been made in our understanding of technology innovations and cost structure optimization of renewable energy. A knowledge gap exists on the other side of the equation – revenue generation. Considering the complexity and stochastic nature of renewable energy projects, there is great potential to optimize the revenue generation mechanisms in a systematic fashion for improved profitability and growth.

This dissertation examines two primary revenue generation mechanisms, or offtake strategies, used in wind energy development projects in the U.S. While a short-term offtake strategy allows project developers to benefit from price volatility in the wholesale spot market for profit maximization, a long-term offtake strategy minimizes the market risk exposure through a long-term Power Purchase Agreement (PPA). With Conditional Value-at-Risk (CVaR) introduced as a risk measure, this dissertation first develops two stochastic programming models for optimizing offtake designs under short and long-term strategies respectively. Furthermore, this study also proposes a hybrid offtake strategy that combines both short and long-term strategies. The two-level stochastic model demonstrates the merit of the hybrid strategy, i.e. obtaining the maximized profit while maintaining the flexibility of balancing and hedging against market and resource risks efficiently. The Cape Wind project in Massachusetts has been used as an example to demonstrate the model validity and potential applications in optimizing its revenue streams. The analysis shows valuable implications on the optimal design of renewable energy project development in regard to offtake arrangements.

OFFTAKE STRATEGY DESIGN FOR

WIND ENERGY PROJECTS UNDER UNCERTAINTY

By

Xinyuan Zhu

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Chapter 1. Introduction

*1.1 **Renewable Energy and Wind Power***

In recent years, controversial issues between the increase of energy consumption and the inevitable environmental impacts have become key incentives for people to propose sustainable strategies to balance the energy use and environmental protection. Energy efficiency and renewable energies are regarded as the "twin pillars" of sustainable energy policy. While energy efficiency is to slow down the energy demand growth and avoid waste of resources, renewable energies are essential to generate more clean energy alternatives so as to make deep cuts in fossil fuel use (Prindle et al. 2007).

Renewable energies, generated from natural resources such as sunlight, wind and water etc., are inexhaustible energies that can potentially substitute traditional sources of fossil fuels to supply final energy consumptions. Since the renewable energies are clean and can be continually replenished through natural resources, they provide substantial reduction for carbon dioxide and other greenhouse gas emissions hence become the most significant potentials to solve the climate change problem we are facing. A long-term plan towards renewable energies use is also regarded as one of the most critical means for many countries to attain national goals such as energy supply diversification, energy security, energy access for the public and the creation of green jobs (SARI 2010, IEA 2010, Lund, Østergaard, and Stadler 2011, Anderson and Winne 2007, Ayres 2008). Furthermore, renewable energy development strategies are increasingly important for the whole world to establish a three-pillar-sustainability, aiming at the balance between the environment, the social equity, and economic demands (UNGA 2005).

Although renewable energy still accounts for a small portion of all energy sources, the deployment of renewable energy, especially in the electricity generation industry, has been developing rapidly in recent years. As of year 2012, renewables accounted for almost half of the new electric capacity installed globally, so that total renewable power capacity worldwide exceeded 1470 GW in 2012, up about 8.5% from 2011 (REN21 2013). It is estimated by the International Energy Association (IEA) with the energy outlook towards year 2035 that although coal remains the backbone of the electricity generation, its share of the mix will be eroded from two-fifths to one-third. Instead, generation from renewable energies will grow to almost three times its 2010 level by 2035; its share in the total energy generation mix will grow from 20% to 31% (IEA 2012b).

Among all the modern renewable energies, wind power receives the most attention. The worldwide cumulative installed wind capacity has witnessed a 25% annual growth rate for the recent two decades (Figure 1-1). Wind power developments are widely acknowledged to have achieved the "mainstreaming" among businesses, governments, consumers, and utilities, especially considering that the majority of annual global investment in power generation is now flowing to renewable energy instead of fossil fuels and nuclear (REN21 2013b, BNEF/UNEP 2012, Schneider et al. 2009).

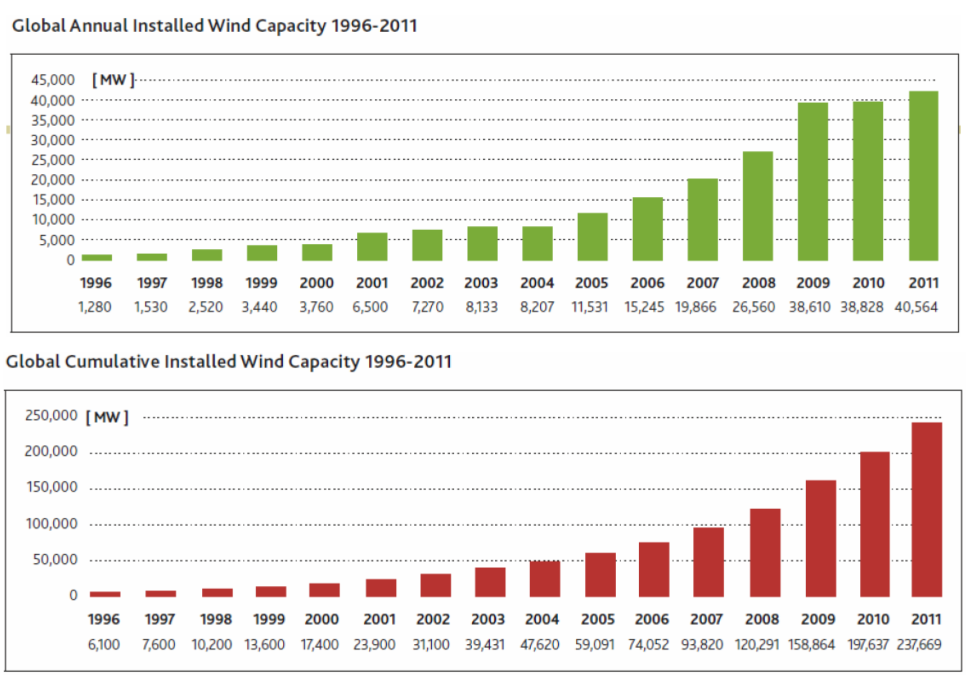


Figure 1-1 Development of Worldwide Wind Energy Generating Capacity (GWEC 2012).

Regulatory schemes are the most important incentives for wind project development and investment. Although the cost for wind projects have decreased dramatically with advanced technology and due to learning curve effect, the wind projects are still in need of external support to be competitive with other conventional power plants (LAZARD 2011). The renewable energy policy schemes in different countries are continuously revised and adjusted, and some of the countries are using multiple approaches.

The most widely used policy incentive is a special price applied to wind power, usually known as the "fixed feed-in tariffs". Such feed-in tariffs are defined by the governments as the power purchase price that local distribution or transmission companies have to pay for local wind power generation that is fed into the network. Fixed feed-in tariffs reduce the financial risk for wind power investors as the power purchase price is basically fixed over at least 10 to 15 years. Feed-in tariffs have been the main driver for wind power in many of the European countries such as Germany, UK and Denmark (GWEC 2012, Ackermann 2012), and they are getting more popular in Asian countries. In India it is called Generation Based Incentive (GBI), applying certain tariff for applied projects (Kumar et al. 2010, GWEC 2012b). Japan and Korea are using an enhanced feed-in tariff in the form of an explicit monetary reward provided for wind-generated electricity, usually paid by the utilities (Van Kooten and Timilsina 2009).

Another typical approach used is a form of quota system with certificate trading for renewable energies. With this approach, utilities are allocated with fixed quotas from the government regarding the amount of renewable energy per year they have to sell via their network. The fulfillment of the obligation is evaluated through the certificate in align with the amount of energy fed into the grid. In European countries it is known as "Fixed Quotas Combined with Green Certificate Trading" or the Renewable Obligation Certificate (ROC) scheme, for example in Italy, Sweden and Belgium (Ackermann 2012, GWEC 2012). Similarly, the Chinese government prioritizes wind energy for selected provinces with the best wind resource and set targets for them (GWEC 2012c). Australia is using a Mandatory Renewable Energy Target (MRET) scheme, requiring electricity retailers to source specific proportions of total electricity sales from renewable energy sources according to a fixed timeframe (GWEC 2012). In the U.S., the Renewable Portfolio Standard (RPS) is a similar quota system, which requires utilities to purchase a percentage of their overall generating capacity from renewable resources.

In addition, various subsidies, grants, rebates and tax incentives are also often implemented to stimulate wind power growth. For example, the U.S. is using the federal Production Tax Credit (PTC) as the major driver for wind power development, providing a tax credit for electricity generated from utility-scale wind turbines. Addition to the PTC, developers can also choose a 30% Investment Tax Credit (ITC) for smaller turbines.

1.2 Wind Power in the U.S. and Its Development Trends

The U.S. is leading the development of renewable energy due to its vast natural resources and advances in technique and project deployment. By year 2012, all the renewable energies capacity developed in the U.S. is around 86 GW, accounting for more than 1/6 of global capacity 480 GW. Among all the new 86 GW renewable power capacities added in 2012, wind energy accounts for the most capacity, for about 70% (60 GW), and has the fastest growing tendency of 39%, followed by solar (30%) and hydropower (25%) (REN21 2013).

Actually, with the terrain suitable for large-scale wind farm development, wind energy has been proved to be an important part in the U.S. long-term energy generation mix strategy. The U.S. accounted for around 21% of the new grid-connected wind turbines worldwide between the end of 2000 and the end of 2012 (GWEC and IRENA 2013). It has been in the top three countries with most installed wind power capacity for over a decade (Ackermann 2012).

Table 1-1 Operational Wind Power Capacity Worldwide. Source: Various edition of Wind Power Monthly and GWEC Global Wind Reports. For 2012 GWEC report, see (GWEC 2012).

Region	Installed Capacity (MW)							
	End-1995	End-2000	End-2002	End-2004	End-2006	End-2008	End-2010	End-2012
North America	1,676	2,695	4,708	7,184	13,062	27,542	44,189	67,576
United States	**1,655**	**2,578**	**4,625**	**6,725**	**11,603**	**25,170**	**40,180**	**60,007**
Canada	21	117	83	459	1,459	2,372	4,009	6,200
Europe	2,518	129,772	21,319	34,401	48,545	65,564	86,272	109,581
Germany	1,136	6,288	11,994	16,629	20,622	23,903	27,214	31,308
Spain	145	2,335	3,337	6,203	11,615	16,754	20,676	22,796
Asia-Pacific	626	1,795	2,606	5,234	11,667	26,012	63,485	97,570
China			470	765	2,604	12,210	44,733	75,324
South and Central America and Caribbean	11	103	137	2,089	508	629	2,010	3,505
Middle East and Africa	13	141	149	225	433	669	1,079	1,135
TOTAL Worldwide	**4,844**	**17,706**	**29,140**	**47,252**	**74,215**	**120,416**	**197,035**	**282,587**

In the year 2008, the U.S. Department of Energy published a groundbreaking technical report named "20% Wind Energy by 2030: Increasing Wind Energy's Contribution to U.S. Electricity Supply", examining the cost, major impacts and challenges associated with the 20% wind energy scenario and comparing it with the scenario which no new U.S. wind power capacity is installed. According to the report, the 20% scenario requires U.S. wind power capacity to grow from 17 GW at the 2008 level to more than 300 GW over 23 years. Over 46 states would experience significant wind development (DOE 2008). New wind power installations would increase to more than 16,000 MW per year by 2018, and continue at that rate through 2030 (Figure 1-2). Updated with the actual new capacity that has been added in recent years (indicated by the red outlines in Figure 1-2), the actual installation capacity is increasing with a stronger trend, and exceeds the projected needed new capacity of the 20% scenario, even in the recession-affected year of 2010.

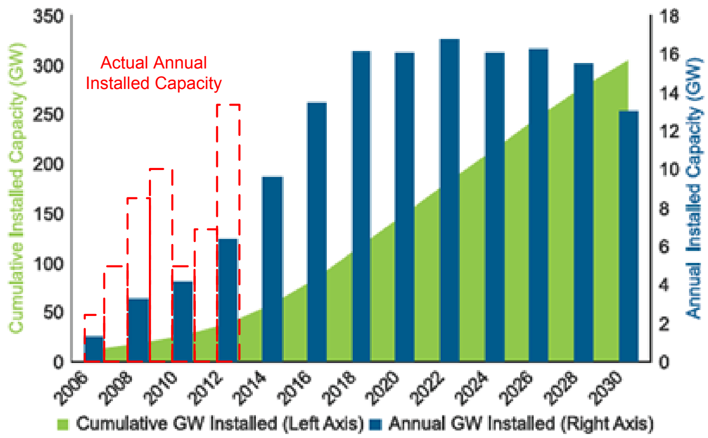


Figure 1-2 Annual and Cumulative Wind Installations by 2030 in the 20% Scenario. Figure adapted from (DOE 2008) and (AWEA 2013b).

The report finds that the U.S. possesses affordable wind energy resources far in excess of those needed to enable a 20% scenario. However, it also points out that the realization of the 20% wind scenario involves major national commitment and planning, as well as overcoming challenges in the areas of technology, manufacturing, transmission and integration, markets, environment and siting, etc. (DOE 2008).

The wind industry in the U.S. has gone through three important phases of development since the 1970s. With the increasing penetration of wind energy, the business models for wind project development gradually changed, and the structure of the U.S. energy industry and electricity market have been influenced correspondingly. Given ambitious expansion goals in the next 30 years, the financing for wind projects is expected to evolve from policy-supported to market-based.

The first phase of wind projects happened before 1992 when a series of federal energy programs were established to deal with the oil crisis and secure the country's long-term energy needs (Sissine 2006). The 1978 Public Utility Regulatory Policies Act (PURPA) required utilities to purchase power, at the utility's avoided cost, from third parties with more environmentally friendly facilities. It was PURPA that created a market for renewable energy independent power producers (IPPs), and successfully made those small-scaled wind producers economically viable (GWEC and IRENA 2013). With constraints in technology and funds, the wind projects developed during that period were small-scale production with capacity less than 1000 kw, with typical wind turbine sizes of less than 100 kw applied in home-use, small facility-use, or at most, small-community use.

The second phase of wind projects was from 1992 to 2008. Enacted in 1992, the federal Production Tax Credit (PTC), was the major driver for wind power developed during that period. PTC provides a certain amount of tax credit for wind energy generated from utility-scale wind project, thus largely promote the development of large-scale wind project. In this phase, the U.S. wind industry rapidly expanded, with the average turbine size reaching 1660 kw by the end of 2008 (Wiser and Bolinger 2012). The installed capacity grew at a compound annual growth rate (CAGR) of 39% from 2004 to 2008 (GWEC 2012, FERC 2009). However, it is worthy notice that the development trend of the wind fluctuated due to an unstable policy climate. With the PTC being expiring on several occasions, there occurred a cycle of strong growth and slowdowns accordingly (Figure 1-3). This policy uncertainty caused loss of investor confidence, under-investment in manufacturing capacity, and variability in equipment and supply cost (GWEC 2012).

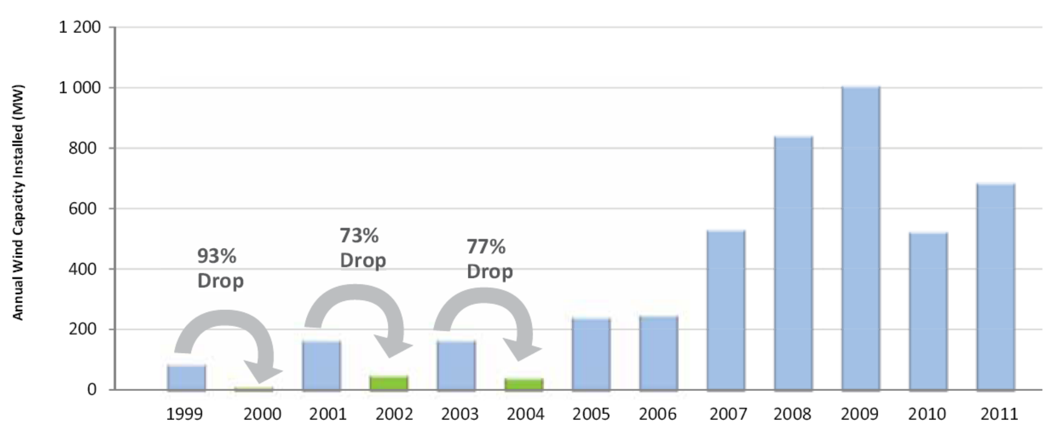


Figure 1-3 Historic Impact of PTC Expiration on Annual Wind Installation (AWEA 2013b).

The wind industry has been undergoing a new phase starting after year 2008, with the key feature of market maturity. Projects are developed with even larger capacity that can grow to several hundred MW, with higher economic scale. Increased rotor diameters and hub heights would be expected to improve capacity factors and project efficiencies (Wiser and Bolinger 2012). The cost has declined due to the advancement of manufacturing and construction technology, as well as increased competition among manufacturers and a shift to a buyer's market (GWEC and IRENA 2013). During this phase, most of the wind power projects are developed by independent power producers (IPPs). According to the DOE wind technology market report, IPPs owned 73% of all new wind power capacity installed in 2011, and 82% of the cumulative installed capacity (Wiser and Bolinger 2012).

In addition to the PTC incentives, Renewables Portfolio Standards (RPS) served as the most popular form of policy supporting the deployment of renewable energy technologies at the state level. With more strict energy requirements from renewable resources, there has emerged a larger and more mature renewable energy certification (REC) trading market, which imposes market-based demand for wind power development. The demand not only comes from utility companies, but a large amount of it also comes from government agencies (such as the Department of Transportation), institutional electricity buyers (such as schools and hospitals), business energy users (such as supermarkets, computer server centers), energy traders and even individual householders. The diversification has brought vitalities to the wind market, and gradually changes the business model for wind energy project development.

Furthermore, some other markets and programs with broader scopes could also influence the development of renewable energy, such as the carbon market, and carbon emission policies. One typical market that is growing is the carbon trading market, with which if the emitters are approaching their quotas, they could try to develop or outsource their business to some clean resources such as wind energy. Although no federal emissions trading market has been established in the U.S., regional markets are in place or are under development, including the Regional Greenhouse Gas Initiative (RGGI), Western Climate Initiative (WCI), and the Midwestern Greenhouse Gas Accord (MGGA).

1.3 Research Needs and Problem Definition for Wind Project Offtake Strategies

As the cost of renewable energy is still relatively high compared to fossil fuels, it remains a critical challenge to make renewable energy cost competitive, without relying on public subsidies. During recent years, many advances have been made in our understanding of technology innovations and cost optimization of renewable energy. There is however a knowledge gap on the other side of the equation – revenue generation. Considering the complexity and stochastic nature of renewable energy projects, there is great potential to optimize revenue generation mechanisms in a systematic fashion for improved profitability and growth.

The offtake of a project is defined as the revenue generation strategy of how the project is selling its product and realizes its profit. The offtake strategy of a project can be an analog to the sales strategy for a company. While profitability remains the primary objective, another important metric of evaluating the strategy is the stability of future revenues. Also, the control of the revenue risk is key for a company's steady development. And for projects, controlling the revenue risk is a guarantee for stable future revenue streams thus can largely increase the possibilities of the projects' success. A well-designed offtake plan will also help to justify the feasibility of the project in the initial phase, enhance the bankability for project financing, and thus essentially reduce the overall levelized cost of energy (LCOE) for wind energy.

If the product of the project is sold through a competitive market, the project offtake strategy deals with the production quantity, selling schedule and price in the market. While if the product is sold through contracts with buyers, then the problem becomes the contract design and negotiation of the detailed terms. As for wind power IPPs, selling the power directly to the market can be treated as short-term offtake strategy, since the decision making in the electricity wholesale market is usually hourly based. On the other hand, signing contract with the buyer is usually a long-term decision. Current power purchase agreements (PPA) typically have contract terms effective for 5-25 years.

Short-term spot market offtake and long-term PPA are both viable for wind projects, and sometimes can be combined. According to the American Wind Energy Association's (AWEA) annual market report, 85% of the wind power capacity installed by Independent Power Producers (IPPs) in 2012 was contracted under long-term power purchase agreements (PPAs), and 15% was sold in the short-term spot market (AWEA 2013b).

Either option has its own pros and cons, thus why there is a market preference for the selection, how to specifically apply them, and whether there is a more efficient way to combine and balance the trade-off between the two is the key questions. The three main questions to answer through this dissertation can be identified as:

1. How should wind IPPs operate when they are participating in the electricity wholesale spot market?

In the U.S. deregulated power market, wind Independent Power Producer (IPPs) are regarded as generating companies (GENCOs), and are obliged to follow the rules of the Day-Ahead (DA) forward market and the Real-Time (RT) balance market. For traditional power plants such as coal and nuclear plants, their strategies are to maximize profit by bidding generation amounts and schedules based on their own manufacturing cost and estimation of the market supply-demand equilibrium (Borenstein 2000). For wind IPPs, since the generation amount solely depends on the actual wind resource, the bidding strategy they make in the forward market could incur high uncertainties when they realize their profit. In practice, wind IPPs usually bid at the 50 percentile of their generation estimation for maximizing their expected profit, but they fail to consider the possible risks and the corresponding probabilities. In Chapter Three of the dissertation, a more general optimization model is proposed to design wind project bidding strategies under uncertainty. The metric of Conditional Value at Risk (CVaR) is proposed as the measure to the project revenue risk. The project developer is expected to adjust their bidding strategies with uncertainties taken into consideration.

2. How should wind IPPs design the Power Purchase Agreement (PPA) as their long-term offtake strategy?

As shown in the AWEA annual market report, more wind IPPs choose PPA as their strategy, this is not only because they will get a promised offtake, but also because they are expecting more stable cash flow streams. However, in practice, there lacks a systematic method for project developers to analyze their negotiation position, and sometimes they have to accept some onerous terms requested by power purchasers so as to sign off as much offtake as possible to get the project started (Umanoff 2008). Furthermore, the traditional approach for valuing a PPA is to take the projected annual cash flow based on the forecasted electricity price and the cost, and then discount the expected future profits by the cost of capital of the investing firm. The project's feasibility is then evaluated by comparing the profit with the initial cost (Deng 1999). This so-called discounted cash flow (DCF) approach becomes inappropriate for the wind project, especially in the deregulated electricity industry because (1) it doesn't address the uncertainty of the wind resource, which have seasonal trend and can be fluctuating severely within a year; and (2) it doesn't capture the volatility of the market electricity, which can be treated as the opportunity cost for the wind project. In Chapter Four, these two problems will be addressed and a modified stochastic programming model will be proposed to seek the optimized long-term PPA offtake strategy, considering the discounted cash flow, CVaR of the profit risks, and a chance-constraint related to the market value of the electricity production.

3. Is there a more efficient way for wind IPPs to combine short-term and long-term offtake strategies, and balance the profit and risks?

With the previous two strategies, wind IPPs either choose a short-term offtake in the spot market, or sign long-term PPAs with purchasers, there is no flexibility to opt between the two. Although some large wind projects are divided into small sub-projects, and are allocated to different offtake strategies, the wind IPPs still have no control over the offtake approach for each sub-project. In an uncertain environment, however, it is important to hold options during the operation so as to balance or hedge against different scenarios due to volatile exogenous factors (Birge and Louveaux 2011). In Chapter Five, an extended hybrid model is presented, which enables the wind IPP to establish a more flexible mechanism for his wind production offtake. A two-level stochastic model is built, with the first level to design the PPA contract with detailed terms before the project starts, and the second level to optimize the allocation of the energy production between the PPA and the spot market. This recourse process will enable the project developer to take into consideration of the uncertainties on the weather and the power market during the operation, and make contract design and negotiation accordingly.

1.4 Dissertation Structure and Research Plan

The issues discussed above justify a dedicated research towards the study and design on offtake strategies for wind energy projects. With an extensive problem definition and background review, we extend the research based on three different offtake strategies, namely the short-term, the long-term and hybrid strategy. Each of the strategy types are discussed and modeled in detail for one specific chapter. A single empirical case study is defined and is applied throughout the three strategies, for the purpose of validating different strategies and comparing them with each other. Figure 1-4 outlines the structure of the dissertation, and content for each chapter.

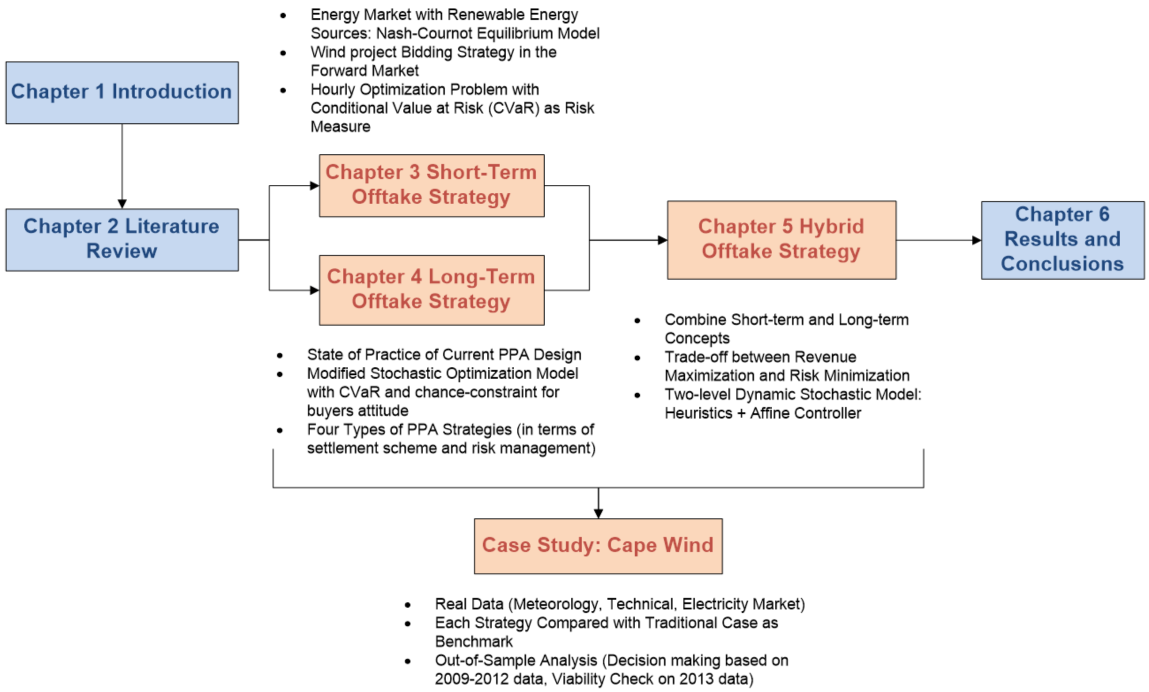


Figure 1-4 Dissertation Structure in terms of Chapter Contents

Although the boundary of this dissertation is defined as a single wind energy project, when building the models, the relationships with the backend, technology-related research and frontend, market-based problems will be considered (Figure 1-5).

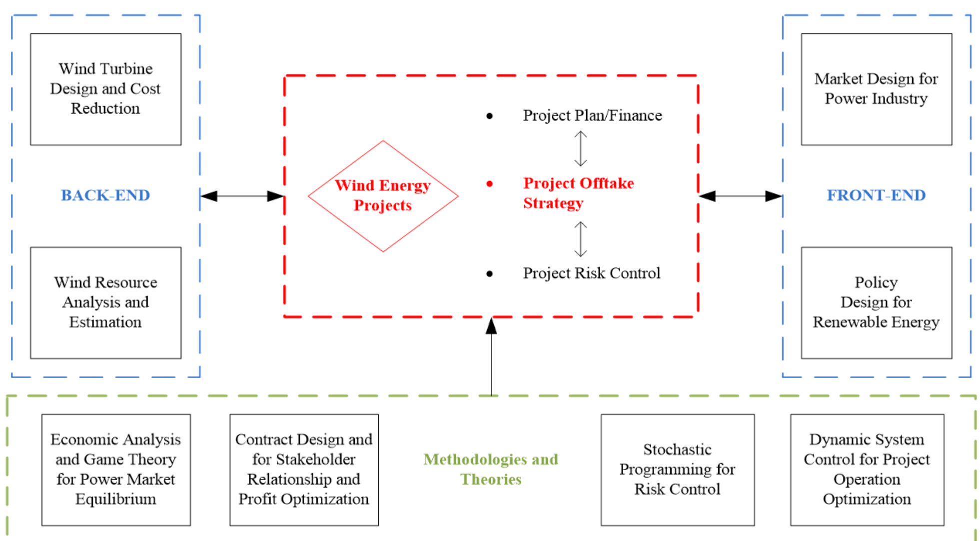


Figure 1-5 Framework for the Research Need and Relative Topics

In particular, the analysis of the uncertainty from the wind resource, together with the wind turbine specifications and its power generation efficiency are key issues associated with the project output risks. Meanwhile, the economic features of the power market and the general political environment are the major impacts that define the value and its volatility of the project's products. On the other hand, the project finance and risk controls during the project operation phase are closely related to its offtake strategies, hence will be specifically discussed and involved in the models. Furthermore, various methodologies are identified to support the research, and mathematical models are built accordingly. For example, a Cournot model is built to depict the electricity wholesale market equilibrium with renewable GENCOs; a chance-constrained stochastic model is utilized to guarantee the no-regret of the PPA buyer; and an affine controller is proposed to quantitatively describe the project operation strategy in the dynamic uncertainties, etc. Detailed processes of methodology selection are discussed in each chapter.

Chapter 2. Review of Literature and Modeling Methodology

2.1 Background for Wind Resource and Wind Speed Profile

Firstly, we would like to review some background of the wind resource, including the formation, the patterns of the wind speed, and the influence factors. These reviews are fundamental information to help build quantitative analysis for wind resource for a certain project. The wind speed varies as a function of time, temperature, height, and other random factors. All these make wind speed appear to be quite random, however, it actually has some distinct features. Therefore, an understanding of these wind speed patterns, and the factors that influence the uncertainties is critical for the evaluation of potential wind energy sites.

The original source of the global winds is caused by solar radiation. The variations in the atmospheric pressure field due to the uneven heating of the earth cause air to move from high to low pressure. Due to the roughness of the ground, the wind conditions near the ground, which is known as the planetary boundary layer, is turbulent (Manwell, McGowan, and Rogers 2002, Ackermann 2012). The characteristics of this boundary layer are directly applicable to wind energy applications (AWEA 1988).

Measuring the intensity of the wind first originated from marine applications. To correlate the wind force scale to real, measurable wind velocity, the World Meteorological Organization (WMO) drafted a standard table, measuring the wind force by the Beaufort scale (WMO 2012). The current generation of wind turbines usually starts operating at a light breeze and will shut down for protection for violent storm or hurricane. In Beaufort terms this would be an operational window between scale 3 and 10 (Table 2-1).

Table 2-1 Beaufort Scale with Equivalent Wind Speed and Description (WMO 2012).

Beaufort	Knots	m/s	WMO description
0	< 1	< 0.2	Calm
1	1-3	0.3-1.5	Light air
2	4-6	1.6-3.3	Light breeze
3	7-10	3.4-5.4	Gentle breeze
4	11-16	5.5-7.9	Moderate breeze
5	17-21	8.0-10.7	Fresh breeze
6	22-27	10.8-13.8	Strong breeze
7	28-33	13.9-17.1	Near gale
8	34-40	17.2-20.7	Gale
9	21-47	20.8-24.4	Strong gale
10	48-55	24.5-28.4	Storm
11	56-63	28.5-32.6	Violent storm
12	> 64	>32.7	Hurricane

The wind patterns associated with height, air pressure, and temperature are relatively straightforward, based on fundamental principles of physics. There are various studies concerning the influence from these factors to the wind patterns (Balmer 1990, Justus 1978, Baumeister, Avallone, and Baumeister III 1978). Of the most importance, the variation of wind speed with elevation is called the vertical profile of the wind speed or vertical wind shear, which directly determines the productivity of a wind turbine on a tower of certain height (Figure 2-1). Scientists are more concerned with the "instantaneous" wind profile which measures the wind affects at different height, and are related via the similarity theory of boundary layers (Schlichting and Kestin 1968).

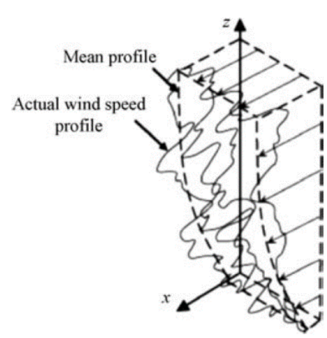


Figure 2-1 Vertical Wind Speed Profile (Van Der Tempel 2006)

Two mathematical models have generally been used to model the vertical profile of wind speed over different terrains (e.g., seas, fields, and forests). Both approaches are subject to uncertainty caused by the variable, complex nature of turbulent flows (Hiester and Pennell 1981). One approach is called Power Law, which assume that the ratio of the wind speed at different height are exponential to the ratio of the height (Schlichting and Kestin 1968), as shown in (2-1):

$$\frac{U(z)}{U(z_r)} = \left(\frac{z}{z_r}\right)^{\alpha} \tag{2-1}$$

Where $U(z)$ is the wind speed at height z, $U(z_r)$ is the reference wind speed at height z_r, and α is the power law exponent. In practice, the exponent α is a highly variable quantity, varies with a lot parameters such as elevation, time of day, season, nature of the terrain wind speed, temperature, and various thermal and mechanical mixing parameter (Manwell, McGowan, and Rogers 2002). Many researchers developed methods to calculate α, while some others feel that the complicated approximations reduce the simplicity and applicability of the power law, hence some more straightforward approached is needed (Justus 1978, Counihan 1975, Spera 1994).

The second approach called Logarithmic Profile, as known as the Log Law, is used by many wind energy researchers. It is based on a combination of theoretical and empirical research, and origins from the boundary layer flow in fluid mechanics and in atmospheric research (Manwell, McGowan, and Rogers 2002). Wortman gave a comprehensive analysis of the methodologies that predict the logarithmic wind profile through the mixing length theory, eddy viscosity theory, and similarity theory (Wortman 1983). The log law is basically used to extrapolate wind speed from a reference height z_r, to another level using the following relationship:

$$\frac{U(z)}{U(z_r)} = ln\left(\frac{z}{z_r}\right)/ln\left(\frac{z}{z_r}\right) \tag{2-2}$$

Different with the power law, this approach introduces another parameter z_0, which represents different surfaces roughness, and can be obtained through experiments. This method can be easily utilized as long as the terrains where the wind projects are proposed to be built are identified. For example, for the offshore wind project, z_0 should be valued at 0.0005m (as Blown Sea, according to the Table 2-2). Then the wind speed that is captured by the anemometers in the meteorology station can be adjusted given the height of the turbine tower, and the actual air flow that is acting on the wind turbine can be calculated accordingly.

Table 2-2 Value of Surface Roughness Length for Various Types of Terrain (Burton et al. 2011).

Terrain description	z_0 (mm)
Very smooth, ice or mud	0.01
Calm open sea	0.20
Blown sea	0.50
Snow surface	3.00
Lawn grass	8.00
Rough pasture	10.00
Fallow field	30.00
Crops	50.00
Few trees	100.00
Many trees, hedges, few buildings	250.00
Forest and woodlands	500.00
Suburbs	1500.00
Centers of cities with tall buildings	3000.00

In order to get a comprehensive analysis for wind resource for a specific project site, meteorology information are needed, such as the wind speed, wind direction, temperature, humidity and so on. In this dissertation, we will use the meteorology station data from National Oceanic and Atmospheric Administration (NOAA) database for the historic wind speed and direction at a 15 min interval (NOAA 2013). The Log Law will be used to estimate the wind resource in terms of the height. And for simplicity, we assume that the other factors such as temperature and pressure do not significantly change the instant wind speed, hence we do not process the original wind data separately for those factors. The indirect influence of those weather factors can be addressed through seasonal wind resource distribution that will be discussed in the next section.

2.2 <u>Energy Output Assessment for Wind Power Projects</u>

When the wind acts on the turbine, the kinetic power of the wind is firstly converted to the mechanical power, the rotational energy of the wind turbine rotor, and then converted to the electricity power through the generator in the wind turbine. Therefore, there are two main components that determine the energy output from a wind project, one is the kinetic power of the wind, and the other is the efficiency of wind turbine design which transfers the kinetic power to the electricity power (Manwell, McGowan, and Rogers 2002).

The kinetic power of the wind can be calculated through the physics formula (2-3), which basically provides the power of an air mass that flow at speed V through an area A (Burton et al. 2011), where $\rho(\mathrm{kg/m^3})$ is the air density, and $V(m/s)$ is the wind speed.

$$P = \frac{1}{2}\rho A V^3 (watts) \tag{2-3}$$

This is the total available energy coming to the turbine. However, the power in the wind cannot be extracted completely by the turbine, the capture of the wind will cause a reduction of speed in the air mass. The theoretical optimum for utilizing the power in the wind by reducing its velocity was first discovered by the German physicist Albert Betz in 1926. According to Betz's Law, the theoretical maximum power that can be extracted from the wind should be discounted by a scale of around 0.59. Hence, even if power extraction without any losses were possible, only 59% of the wind power could be utilized by a wind turbine (Gasch and Twele 2012). Therefore, the power utilized by the wind turbine can be written as:

$$P = \frac{1}{2}\rho A V^3 C_p (\mathrm{watts}) \tag{2-4}$$

Where C_p is called power coefficient, which should be calculated by the feature of the air flow and the wind turbine. For simplicity, we assume C_p to be 0.6 in our calculation.

From (2-4), the energy output varies to the cube of the wind speed, which indicates that the volatility of the energy output is exaggerated accordingly. Therefore, in order to increase the prediction accuracy for the energy output of a wind project, one of the most important research and implication topics in the wind industry is how to better forecast the wind resource of a particular location. It is estimated that the cost due to wind energy prediction error have been as much as 10% of total generator energy income, implying a strong need to manage the risks of unexpected levels of generation (Fabbri et al. 2005).

Comparing with the weather factors mentioned in the last section, the relationship between the wind speed and the time is much more complicated and harder to predict. The wind resource are uncertain with time mainly associated with its intermittency nature due to the orographic conditions and global phenomena (Ackermann 2012). Furthermore, due to the high cost and deficiency of technologies, wind power, similar as other natural resources such as solar and hydro power, cannot be reasonably stored. Therefore in the energy industry, such renewable resources are called variable generations, and draws a lot attentions in the electricity market design field, especially with their higher penetration level to the conventional market (NERC 2010b).

Although forecast techniques are significantly improving over the years, predicting wind's output is much more difficult than predicting the output of conventional generators or load (Pérez-Arriaga and Batlle 2012). The variability of wind speed differentiates with the timeframe they are evaluated, and various approaches are proposed to deal with each of them. Generally, only very near-term wind predictions are relatively accurate (Xie et al. 2011). In particular, it is estimated that the Mean Absolute Error (MAE), which measures the forecast error, for hour ahead forecasts can be about 5-7% of rated capacity; for day-ahead forecasts, the MAE could increases to the range of 12-25% (Milligan et al. 2009, NERC 2010b).

In the literature, there are a number of methods been adopted and developed for wind speed forecasting. Generally, the methods can be classified into three categories, namely, physical models, statistical models, and time series models (Liu, Shi, and Erdem 2010).

Physical models are often referred to as Numerical Weather Prediction (NWP) models, which use equations based on the fundamental principles of physics and simulates the state of atmosphere (Focken and Lange 2006). Since the model is not based on the historical data, but on the real time atmospheric conditions, the results can be relatively accurate (Giebel et al. 2006). And the model could be especially useful in the real-time estimation, or very short time-scale forecast, such as second to minute analysis. On the other hand, these models were originally developed for general weather forecasting purposes (public safety, aviation, agriculture, etc.) rather than specifically for wind forecasting, hence the model itself is a large system and requires great computational efforts (NERC 2010b).

There are many time series approaches proposed for modeling the dynamics of the wind speed processes (Alexandridis and Zapranis 2013). These models are more effective in the short to medium time-scale analysis, such as hour ahead forecasts. The general group of MA (moving average), AR (autoregressive), ARMA (autoregressive moving average), and ARIMA (autoregressive integrated moving average) models are the most common time series approaches used in the wind studies (Liu, Shi, and Erdem 2010). There have been a lot of studies on the use of linear ARMA models to simulate the short-term wind variations (Caporin and Preś 2012, Huang and Chalabi 1995, Billinton, Chen, and Ghajar 1996, Torres et al. 2005). Kavasseri et al. proposed a more sophisticated fractional integrated ARMA (f-ARIMA) model on the day-ahead (24 h) and two-day-ahead (48 h) horizons (Kavasseri and Seetharaman 2009). Ailliot et al. applied an autoregressive model (AR) with time-varying coefficients to describe the space-time evolution of wind fields (Ailliot, Monbet, and Prevosto 2006).

Moreover, some non-conventional time series models such as NN (neural networks), SVM (support vector machines), and fuzzy logic have attracted enormous interests for wind speed forecasting due to their capability of implicitly establishing the complex non-linear relationship between variables (Kariniotakis, Stavrakakis, and Nogaret 1996, Pourmousavi Kani and Ardehali 2011). Sfetsos conducted a comparison of various time series models on daily wind speed forecast, and found out that artificial intelligence based models outperformed the linear models, and a Neural Logic Network that incorporated Logic Rules realized the least error (Sfetsos 2000). Li et al. compared three types of typical neural networks, namely, adaptive linear element, back propagation, and radial basis function, and concluded that the performance of the model is dependent upon the data sources, and for different models, the optimal solution can vary from each other, as much as 20% in terms of one particular evaluation metric (Li and Shi 2010).

For medium to long timescale wind analysis, such as the monthly forecasting, the purpose is more focused on capturing the statistical trend of seasonal characteristics. There are several studies regarding the long-term (usually more than a year) variations of the wind resource, and it is found that the seasonal distribution of wind speed is significant (Petersen et al. 1998, Soder and Amelin 2008). For example in the Figure 2-2, the historic wind speed data is plotted on the daily base for the U.S. offshore Cape Wind project. As in this four year period (from 2009/03 to 2012/12), the wind speed almost follow the identical pattern within a year: the wind blow harder in autumn and winter, and is relatively calm in spring and summer. There are some even longer-term analysis estimated that the variation of the yearly mean power output from one 20-year period to the next has a standard deviation of 10% or less (Ackermann 2012). Hills compares the different natural sources and indicated that in many places, the uncertainty regarding the availability of water over a longer time period (more than one year) for hydropower generation exceeds that of wind power (Hills 1996).

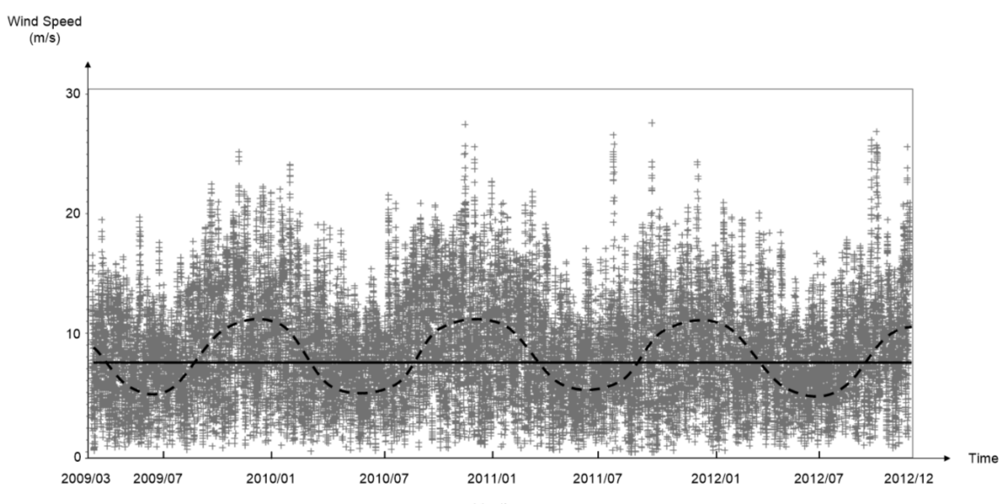


Figure 2-2 Seasonal Trend of Wind Speed Distribution of Cape Wind Project

Based on the abundant studies and numerical analysis on the long-term trend of wind speed, it is usually assumed that over the lifetime of a wind turbine (usually about 20 years), the uncertainty of the wind resource at a monthly base is not large (Ackermann 2012). It is because of this feature makes it possible and reasonable to use basic statistics distributions to depict the monthly wind resource, sometimes even applied on daily or hourly wind speed too (Daniel and Chen 1991, Garcia et al. 1998). Even though there is also much debate at present about the likely effects of global warming that could affect long-term wind climates trend in the coming decades, for simplicity, this dissertation will follow the conservative assumption that daily and monthly wind resource can be reasonably estimated by distributions regretted from the historic data (Burton et al. 2011, IPCC 2007, 2012).

In literature and practice, there are two most commonly used distributions, namely the Rayleigh and the Weibull distribution, which are applied to estimate the wind speed. Figure 2-3 displays the typical pdf of Rayleigh distribution and Weibull distribution. The Rayleigh distribution is the simplest speed probability distribution to represent the wind resource since it requires only a knowledge of the mean wind speed $\bar{V}$. The Weibull distribution is based on two parameters, k (a shape factor) and c (a scale factor), both of with are function of the mean wind speed $\bar{V}$ and the standard deviation of wind speed σ_V. Hence the Weibull distribution can better represent a wider variety of wind regimes (Manwell, McGowan, and Rogers 2002). Justus et al. first proposed to use the Weibull distribution to estimate wind speed, and apply it to the actual observed data. They concluded that Weibull distribution give smaller fitting errors than some other distributions and can be used to project wind speed at another height (Justus et al. 1978). Brown et al. put forward a general model applying these two non-Gaussian distribution, and simulate the hourly wind power for the National Aeronautics and Space Administration (NASA) (Brown, Katz, and Murphy 1984). Although there are some other distribution proposed to deal with the wind speed, such as lognormal distribution (Garcia et al. 1998) or the Chi-square distribution (Dorvlo 2002), Weibull distribution is widely accepted and utilized in the researches and empirical studies (Tuller and Brett 1984, Celik 2004, Jaramillo and Borja 2004).

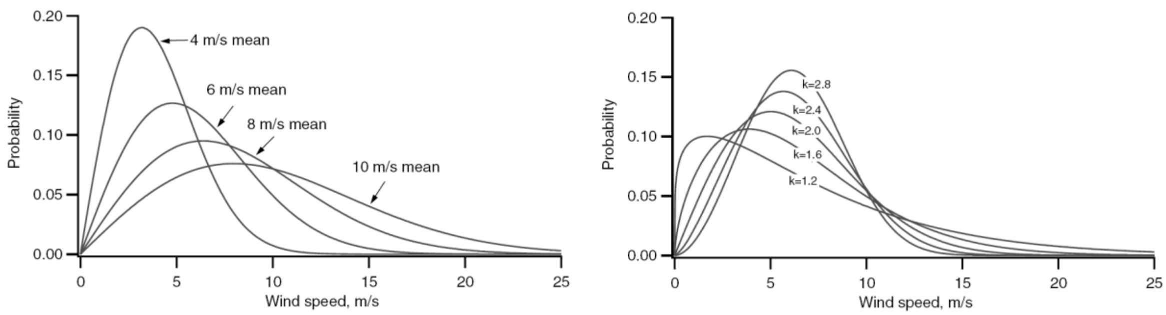


Figure 2-3 Rayleigh Distribution and Weibull Distribution with $\bar{V}$=*6m/s*. Source: (Manwell, McGowan, and Rogers 2002)

Figure 2-4 shows a typical wind speed probability density function shape, which deviates significantly from the normal and is not symmetrical (Alexandridis and Zapranis 2013). It is usually in the range from 0 to 30 m/s, and has positive skew with longer tail to the right.

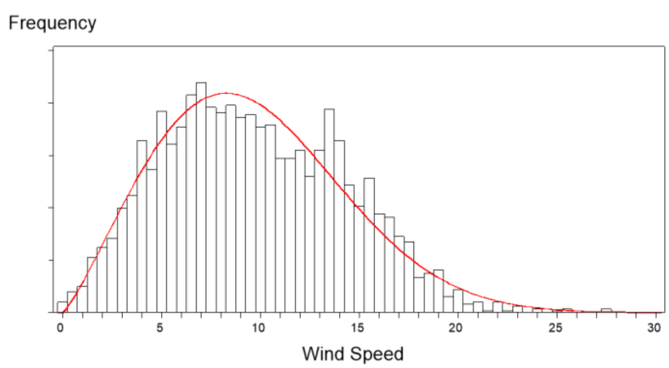


Figure 2-4 Wind Speed pdf for Cape Wind Project in October

Given the wind power that acts on the wind turbine, there is another important issue that determines the energy output from the system, the efficiency of the power generation. Wind turbine does not generate electricity all the time, instead, the efficiency at different wind speeds varies significantly. Each individual wind turbine has a specification for the relationship of its power generation and corresponding wind speed, which is called the power curve. Figure 2-5 is the power curve of the offshore Cape Wind project turbines SWT-3.6-107, manufactured by

Siemens (Siemens 2011). Typically, the wind turbines start to generate electricity at the speed which is called the cut-in speed, ranging from *3-5 m/s*, and stops production at the cut-out speed, ranging from *20-25 m/s*. The most efficient range is from the cut-in speed to the rated speed, with which the power generation follow the cube relationship, as discussed in equation (2-4). Once reach the rated speed, the maximum power production will be limited, or, in other words, some parts of the available energy in the wind will be 'spilled' (Ackermann 2012). Typical rated power ranges from *12-16 m/s*, and the power output at the rated speed is the wind turbine's nameplate capacity, which is 3.6 MW for the Siemens turbine in the example (Figure 2-5).

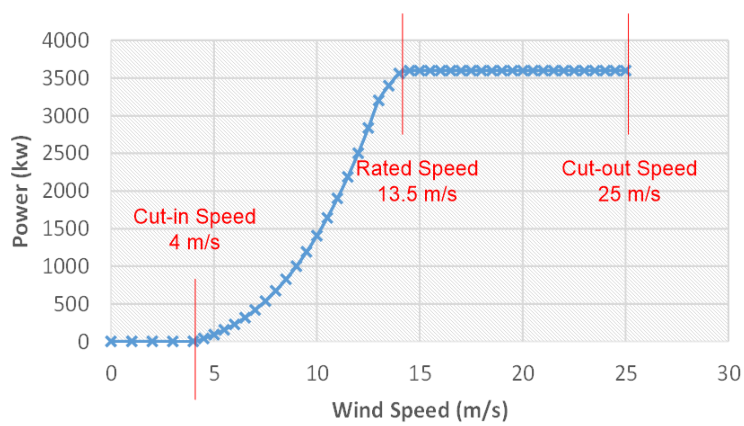


Figure 2-5 Power Curve for Wind Turbines of Cape Wind Project. Data source: (Siemens 2011).

As discussed, the uncertainty of the power generation not only depends on the volatility of the wind, but also on the relationship between the wind and the specific turbines. One specific metric which is called Capacity Factor (CF) is then proposed to measure the performance of a specific wind turbine or multiple wind turbines as a project:

$$CF = \overline{P_w}/P_R$$

The capacity factor of a wind turbine at a given site is defined as the ratio of the energy actually produced by the turbine to the energy that could have been produced if the machine ran at its rated power P_R, over a given time period (Manwell, McGowan, and Rogers 2002).

2.3 *Evaluation for Project Revenue Risks*

In order to quantitatively evaluate the balance between the revenue and risks, a critical challenge is to identify a metric to measure the risks, in dollar value to be comparable to revenue.

Typically in the domain of finance, the most classic approach for managing risks is the mean-variance framework, with which the objective is to maximizing the expected risk premium per unit of risk (Markowitz 1952). Since then, the modern portfolio theory has been developed greatly and applied in various situations (Chopra and Ziemba 1993, Crama and Schyns 2003, Hirschberger, Qi, and Steuer 2007, Konno and Suzuki 1992). However, using the variance/standard deviation as the measure for risks implies that investors weight the probability of negative returns equally against positive returns (Campbell, Huisman, and Koedijk 2001). It may have a potential danger to sacrifice too much expected return in eliminating both high return extremes and low return extremes (Huang 2008, Markowitz 1952).

Semi-variance and Value-at-Risk (VaR) were then proposed as alternatives for measuring the risks. Both approaches are able to measure the left-side tail for the return. Value-at-Risk (VaR), defined as the upper percentile (for instance, 95%) of the loss distribution, has been widely used as a simple and easy representation for high losses (Krokhmal, Palmquist, and Uryasev 2002, Jorion 1997). For example, the Basel Committee on Banking Supervision, the U.S. Federal Reserve, and the U.S. Securities and Exchange Commission have all converged on VaR as the benchmark risk measure to maintain the minimum level of capital as reserves against financial risks (Jorion 1997).

However, one important drawback of VaR is that it is only efficient when the underlying risk factors are normally or log-normally distributed. Hence, most approaches to calculate VaR rely on linear approximation of the portfolio risks and assume normal or a joint normal (log-normal) distribution of the underlying market parameters (Simons 1996, Pritsker 1997, Duffie and Pan

1997). For non-normal distributions, VaR may have undesirable properties, such as lack of sub-additivity and convexity, and incoherent.

Therefore, as a more advanced alternative for risk measurement, Conditional Value-at-Risk (CVaR) was then proposed and is gaining its popularity. Although CVaR has not become a standard methodology in the finance industry, it has been proven to have better mathematical properties than VaR, such as transition equi-variant, positively homogeneous, convex, monotonic (Pflug 2000, Rockafellar and Uryasev 2000). Furthermore, with the technique proposed by (Rockafellar and Uryasev 2000) which calculates VaR and optimizes CVaR simultaneously taking into shape, CVaR is ready to be combined with analytical or scenario-based methods to be applied in optimizing risk controls for all different industries (Krokhmal, Palmquist, and Uryasev 2002).

We will apply the concept of CVaR as the measure for risks throughout the whole dissertation, and the technique which defines a so-called F function will be utilized to mathematically transform the optimization problem to a solvable linear programming. Detailed definition for CVaR and the derivation for the F function are summarized in Appendix A.

Chapter 3. Offtake Strategy for Wind Projects in Short-Term Power Wholesale Market

3.1 Introduction

With higher penetration of renewable energies, the structure of the power system is changed accordingly in terms of its supply-demand equilibrium and the allocations of different sources of power supplies. Hence the short-term power offtake strategy for renewable projects to be integrated into the existing power market needs to be scrutinized.

In the U.S. deregulated power market, wind Independent Power Producer (IPPs) are treated as generating companies (GENCOs), and are obliged to follow the rules of the Day-Ahead (DA) forward market and the Real-Time (RT) balance market. Although there exist numerous research and mature decision systems for the traditional power plants to arrange their production and offtake plans (Carrión et al. 2007), the strategies need to be reconsidered and designed specifically for wind projects, due to their overarching attributes that are different from traditional power plants:

1) Low Variable Cost

Wind power has high up-front cost (investment cost) and fairly low variable cost. Because most of the variable cost come from annual fixed expenses, such as insurance and regular maintenance, the marginal running cost, which are usually fuel cost for traditional resources, are seen to be very low, even zero (Ackermann 2012).

2) Uncontrollable Generation Quantity

Sine wind power is a natural source, once a project is designed with a fixed structure and capacity, the power generation quantity is mostly dependent on the sufficiency of the wind energy. The magnitude and timing of variable generation output is less predictable than for conventional generation (Ellis et al. 2012). The only controllable variable from the project owner side is the availability of the system, which is usually maintained as high as about 98% for offshore wind projects.

3) Intermittent Nature

Wind power is an intermittent energy source which is not easy to predict. The daily and hourly variations are significant, which introduces a high uncertainty in the availability of wind-generated power even within relatively short time horizons (NERC 2010a). As a result, the energy output from the wind project fluctuates on all time scales (Ellis et al. 2012).

For traditional power plants such as coal and nuclear plants, their strategies are to maximize the profit by making bidding plans for the generation amount and schedule based on their own manufacturing cost and estimation of the market supply-demand equilibrium. For wind IPPs, since all the generators are price-takers and they have very low generation cost, it becomes obvious that they will just try to sell as much as they generate at the given price. However, since the generation amount solely depends on the actual wind resource, the bidding strategy they make in the forward market could result in significantly high uncertainties when they realize the profit in the real-time market, together with the volatility of the electricity spot price. In practice, wind IPPs usually bid at the 50 percentile of their generation estimation for maximizing the expected profit. The failure to consider the possible risks and the corresponding probabilities is the main reason why the project developer cannot justify the sustainability, and why the investment parties are concerned that the current short-term strategy could undermine the overall project profitability.

In this chapter, we will propose a general optimization model to design wind project bidding strategy under stochastic environment. A metric of Conditional Value-at-Risk (CVaR) is proposed as the measure to the risks of project revenue. The project developer is expected to adjust their bidding strategies with uncertainties taken into consideration. Essentially, the uncertainties come from four parts: the uncertain wind resource, the uncertain electricity price, the forecast error of wind resource, and the differences of electricity price between the day-ahead market and real-time market.

*3.2 **Deregulated Power Market***

In April, 1996, the Federal Energy Regulatory Commission (FERC) of the U.S. issued order No.888 and order no. 889, which were known as the deregulating or restructuring of US electric industry, which "promoting wholesale competition through open access non-discriminatory transmission services by public utilities" (FERC 1996a) and "establishing and governing an Open Access Same-time Information System (OASIS) (formerly real-time information networks) and prescribing standards of conduct" (FERC 1996b). Prior to the deregulation, the U.S. electricity market is a command-and-control industry. The energies are generated, transmitted and distributed by vertically integrated entities, who own and control the whole system subject to full regulation. Electricity consumers, on the other hand, had little or no choices regarding the sources of electricity they are buying.

The deregulated market was established aiming to maintain a long-term consumer welfare, which relies on a complete competitive electricity wholesale market, providing a platform with competition to draw efficient investments in new generation and to better manage the operation capacity. Some basic economic efficiency criteria are proposed when the market was taking into shape, including “bid-based”, “security-constrained”, and “economic dispatch with nodal prices” (Hogan 1997). In order to meet the criteria, Independent System Operators (ISOs) and Regional Transmission Organizations (RTOs) were established to coordinate, control and monitor the operation of the regional electrical power system. Figure 3-1 is the map of nine North American ISOs/RTOs. All these ISOs and RTOs serve two-thirds of electricity consumers in the United States and more than 50 percent of Canada's population (Council 2011). Some of their operation zone covers a large geographic area with multiple states, while some regulate a single U.S. or Canadian State.

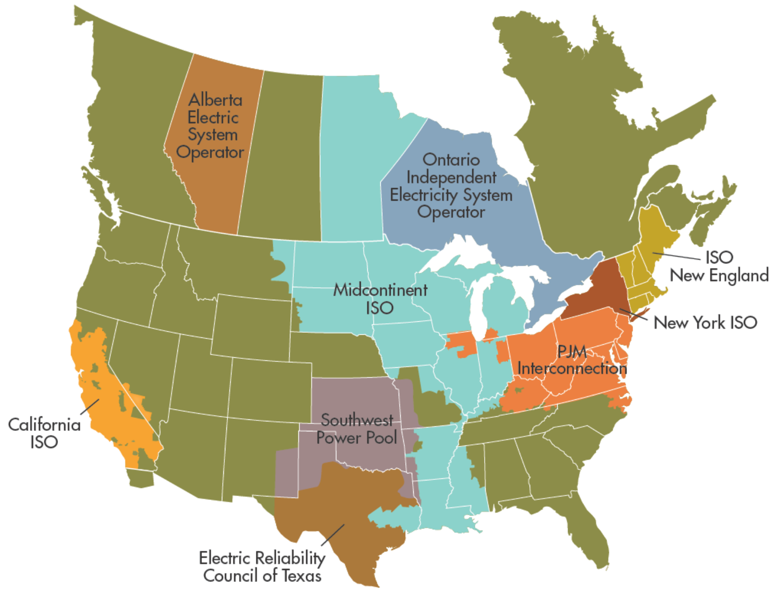


Figure 3-1 Nine Major North American RTOs/ISOs (Council 2011).

ISO/RTOs play important roles in the deregulated power market. As a matter of fact, without such independent entities as ISO/RTOs, the independent operation of the grid cannot be guaranteed. In the power market operation, ISO/RTOs are required to be working as independent middlemen between individual market participants, such as transmission companies (TRANSCOs), generation companies (GENCOs), distribution companies (DISCOs), and end-users. In order to operate the competitive market efficiently while ensuring the reliability of a power system, the ISO/RTOs establish sound rules on energy and ancillary services markets, manage the transmission system in a fair and nondiscriminatory fashion, facilitate hedging tools against market risks, and monitor the market to ensure that it is free from market power (M. Shahidehpour 2002, Shahidehpour, Yamin, and Li 2002).

GENCOs are entities that operate and maintain existing generating plants. They may own the generating plant or interact on behalf of plant owners with other entities. The GENCOs have the opportunity to sell electricity to the power market, from which large customers such as DISCOs and aggregators may purchase electricity to meet their needs. GENCOs may also opt to sell electricity to entities with whom they have negotiated bilateral power purchase contracts (M.

Shahidehpour 2002). In the electricity wholesale market, GENCOs are participating as electricity suppliers, selling their product to meet the demand from the buyers to realize the trading. Before the market deregulation, GENCOs typically shared the ownership or affiliation with other market participants, such as DISCOs (usually known as electricity utilities). While with the Energy Policy Act of 1992 (EPAct), and a series of orders issued in 1996 and 2000, the U.S. Federal Energy Regulatory Commission (FERC) mandated that utility-owned transmission systems be openly accessible to wholesale generators. Thereafter, Non-Utility Generator (NUGs), known as Independent Power Producers (IPPs) grew dramatically (Zatzman 2012). The introduction of IPPs contributes greatly to the diversification of both the supply and nature of energy production, assists in the introduction of new skills and capital into the industry, and improves the benchmarking of performance and pricing (Eskom 2013). Although IPPs are typically smaller in size comparing with utility-owned GENCOs, they are specifically suitable types for developing renewable energy projects. In fact, the development of wind projects in the U.S. is predominantly driven by IPPs (Hahn and Gilman 2013).

In order to design an efficient market to realize the reliability and the sustainability, theoretic models evolve quickly through the power market restructuring process, and two major market branches emerged and were implemented for various markets in the United States (Wilson 1999). One is the short-term wholesale market structure, sometimes is also called a PoolCo market, which is essentially built with a centralized pool where buyers and sellers are competing for the resources, and the power are produced and dispatched with a single (spot) price based on some economic rules (M. Shahidehpour 2002, Shahidehpour, Yamin, and Li 2002). The other one is a bilateral structure, where buyers and suppliers are negotiating and signing bilateral power purchase contract by themselves with desired contract terms. Both these two structures have their pros and cons, and there should be different strategies for IPPs to participate in different branches.

In this chapter, we will first discuss about the offtake strategy for wind projects in the short-term wholesale market, and the long-term bilateral relationship will be analyzed in the next chapter.

3.3 Trading Scheme of the Short-term Power Wholesale Market

Among the many economic tools for maintaining the competitive market and mitigating market power, such as monopoly and monopsony, is a two-settlement approach where day-ahead forward transactions, and real-time balancing transactions are settled sequentially at different prices. Hence there was established two markets constructing the short-term equilibrium, the Day-Ahead Forward Market (DA for the abbreviation), and the Real-Time Balancing Market (RT for the abbreviation). Figure 3-2 shows the decision process of the two markets.

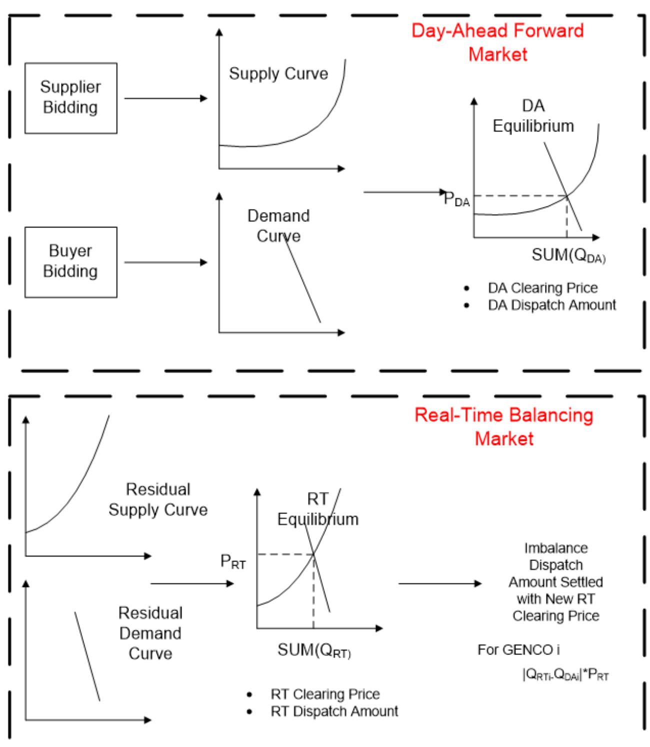


Figure 3-2 Decision Process of the DA and RT markets

The DA market is a forward market for scheduling resources at each hour of the following day (M. Shahidehpour 2002, Shahidehpour, Yamin, and Li 2002). Buyers and suppliers offer and bid for the electricity, with the price and amount, based on their own strategy, and get virtually dispatched based on ISO/RTOs' decision about the clearing price (a single price for all participants in the same location for each hour) and respective amount for the specific hour. The dispatch schedule in the forward market are financially and physically binding, which means the scheduled suppliers must produce the committed quantity or, otherwise, buy power to balance their positions at the actual delivery time point. Likewise, wholesale buyers of electricity pay and lock in their rights to consume the quantities cleared at the forward prices.

To ensure the reliability of power systems, the production and consumption of electric power must be balanced in real-time. However, real-time values of load, generation, and transmission system can differ from forward market schedules. Therefore, the real-time market is established to meet the balancing requirement, that's why it is also called balancing market. In the real time, the imbalance, both for the supply and the demand side, will be reconciled based on the real-time equilibrium in terms of the RT clearing price, and the dispatch amount for each GENCOs. The ISO/RTOs act as important intermediates or facilitators between supply and demand in the balancing market.

The two-settlement system is designed to recognize the critical characteristics of the power system, to operate the power system efficiently, and to utilize prices and associated incentives that are consistent with efficient operation (Hogan 2002). Theoretical analysis and empirical evidence suggests that forward trading reduces the incentives of sellers to manipulate spot market prices by reducing the vulnerability of seller's profits to spot price fluctuations. Thus, forward market is viewed as an effective way of mitigating market power at real time (Kamat and Oren 2004).

There are numerous theoretical practical researches about electricity pricing. Given cost of all GENCOs on the network, demand and network topology, (Schweppe et al. 1988) originated the theory of competitive electricity locational spot prices using an optimal power flow model, with the objective of minimizing the total cost of generations. In the later studies, supply function competition (Klemperer and Meyer 1989) and Cournot-Nash Equilibrium (Hashimoto 1985, Harker 1986) are two types of conjectural variations models used to represent energy markets. Green used supply function equilibrium to describe the electricity spot market in England and Wales soon after deregulation (Green 1999). He depict the situation when each firm submits a non-decreasing supply function specifying the quantity it is willing to provide at a given price, and solve the supply function equilibrium (SFE). Bolle considers the reaction of consumers to the average spot prices, and finds a continuum of equilibrium in all cases (Bolle 1992). He then extends the earlier research to consider command side bidding, and finds that increasing number of suppliers and demands results in more competitive behavior (Bolle 2001). Smeers and Wei assumes the market to be a Cournot competition and proposes a spatial oligopolistic electricity models to study the opportunity cost transmission prices (Smeers and Wei 1997). They further expanded their models to consider the regulated transmission prices and solve the Nash equilibrium by developing spatial models for the electricity market (Jing-Yuan and Smeers 1999). Hobbs assumes linear demand and cost functions, and establishes a mixed linear complementarity problem for solving Cournot market equilibrium in the bilateral and centralized PoolCo power market (Hobbs 2001).

In a competition power market, it is usually assumed that sellers and buyers are very small compared to the market size, therefore, no participants can significantly affect the existing market price through their bidding behavior. In addition, each generation company plays a Nash game in the quantity they are bidding, which is equivalent to the situation where GENCOs are assuming that other firms will not alter their outputs — a Nash-Cournot game (Hobbs 2001). The bidding strategies then can be obtained by deriving first order of different GENCOs' payoff function and market clearing conditions and solving them simultaneously. A solution satisfying these conditions will have the property that no participant will want to alter its decisions unilaterally, reaching a Nash equilibrium. Smeers concludes his survey of gas and electric market models by arguing that explicit statement and solution of equilibrium conditions is a promising theoretical and computational approach to modeling strategic behavior (Smeers 1997).

Given the information from all offerings and biddings, the spot price at which each participant can sell or buy electric power is essentially given by the equilibrium where supply meets demand, and ISO/RTOs are responsible for declaring and adjusting the price, as well as the dispatching schedule to maintain a fair and economically efficient market. In the day-ahead market, the price is calculated on an hourly interval, and is usually comprised of three parts: the energy price, the congestion cost, and marginal losses. Typically, the energy price remains the same in the whole power system, while the congestion price and marginal losses depend on the topology of the grid network, and constraints of the transmission capacity. The latter two are much smaller comparing with the energy price part. For simplification, we assume there is no congestion cost or marginal losses, hence the total price remains the same for all GENCOs in the system. The clearing price is called locational marginal pricing (LMP) or nodal pricing, and theoretically is the shadow price or dual price reflecting the increase of total cost of the market with relaxing one unit for each corresponding constraints for different participants (Litvinov 2011, Schweppe et al. 1988). In the scheme of LMP, generation is dispatched from the lowest bidding price, and then the next and so on until the supply and demand are met. In the Nash-Cournot equilibrium case, GENCOs usually assume that others will not alter their sales, hence they make their decisions based on their marginal generation cost. Therefore, the LMP scheme can be treated as the price discovery mechanism that the generation dispatch is in a merit order of cost of production, which first dispatches the generation from the least marginal cost GENCO, and then the next and so on.

In practice, the LMP has been used in many deregulated markets, most notably in the east coast of the U.S. power market, such as the PJM Interconnection, New York, and New England markets. Figure 3-3 is an example of the supply and demand curve for a typical deregulated power market. Once the facility is built, the marginal cost of production mainly represents the cost for fuel. Hence for wind and other renewable energies, the marginal cost of production can be regarded as very small, or even negative, if considering the credit or subsidies. Therefore, as shown, the bids from wind power and nuclear enter the supply curve at the lowest level owing to their low marginal cost, followed by CHP plants, while condensing plants and gas turbines are those with the highest marginal cost of power production (Ackermann 2012). In general, the demand for power is highly inelastic, which means the demand is not sensitive to the change of the supply.

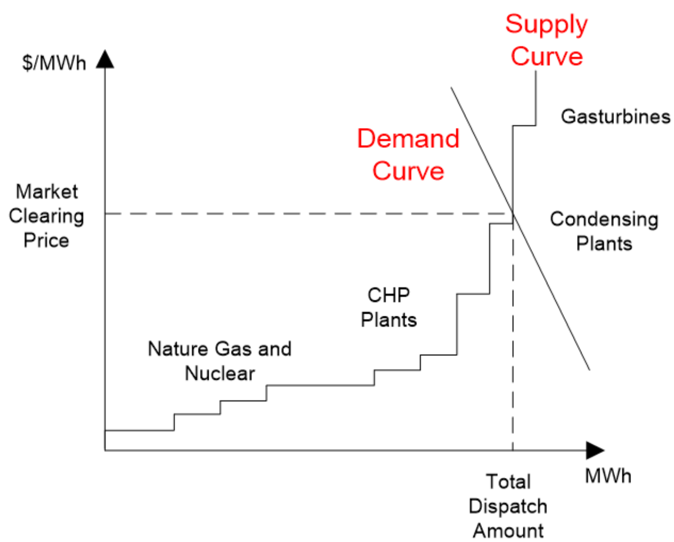


Figure 3-3 Supply and Demand Curve of a Deregulated Power Market. Adapted from (Ackermann 2012).

In the DA market, bidding and offering are regarded as virtual trading, which helps buyers and suppliers to lock the price for the specific hour in the second day, and hedge the price volatility. While in the Real-Time market, the trading are real transactions and transmissions. GENCOs materially deliver the electricity they generate to the grid and distributors and utilities get the power from the grid. ISO/RTOs facilitate the real-time equilibrium, by updating the information from the actual supply and demand, sending price signals to both parties, and declare real time clearing prices. According to the hourly scheduled RT LMP, GENCOs get settled for their RT generations. For a well-organized power market with no market power, the RT LMP should not deviate too much from the DA forward LMP. Figure 3-4 is a typical plot for DA LMP and RT LMP from PJM's market report (PJM 2012). As shown, RT LMP is greater than DA LMP for about 12 hours out of 24 hours in a day.

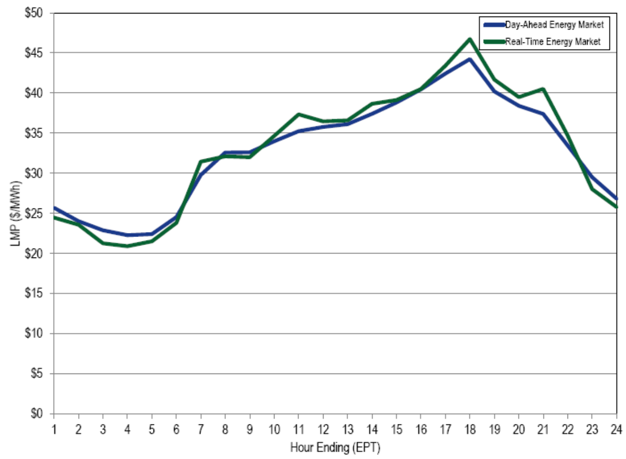


Figure 3-4 RT LMP and DA LMP for a typical day in PJM market (PJM 2012).

The RT balancing market is a flexible mechanism that helps to adjust the imbalance supply and demand from the forward market. Here are some examples of how it works:

If the RT supply is larger than the RT demand, then the RT LMP will be larger than the DA LMP. This is an incentive for GENCOs to increase their generation capacity to meet the demand, because the marginal cost is less than the marginal profit, assuming in the forward market, GENCOs are bidding at their marginal cost.

Similarly, if the RT supply is less than the RT demand, then the RT LMP will be less than the DA LMP. In this case, the GENCO that is with the highest marginal cost will have the incentive to reduce its generation, since the penalty of not fulfilling the bidding amount will be less than the saving from reducing the generation.

If supply and demand remain the same, but some of the GENCOs cannot fulfill the obligation, then there will be additional supply requirement from other GENCOs. Then the RT LMP, which is the marginal cost of the additional supply is expected to be larger than the DA LMP. The DA LMP is settled as penalties for the GENCOs that fail to meet promise, and is larger than marginal cost for those GENCOs.

Same situation happen to the GENCOs when they generate more than they bid, then there is extra supply than demand, causing the RT LMP decreasing, then there will be a lost accordingly. In these two cases, there is no incentive for GENCOs to unilaterally change their generation unless they have to.

All these rules apply to the wind IPPs, but it is more complicated because they have no control over their generation. Once they bid in the forward market, their real time settlement will be purely dependent on the actual wind resource. Their strategies, unlike other traditional GENCOs, will be to decide how much they bid in the DA market, based on their forecast, instead of their actually generation. Detailed decision making process will be discussed in the following part.

3.4 <u>Offtake Strategy in the Energy Wholesale Market for Wind Projects</u>

We now consider the situation where the wind IPP sells all its power generation to the energy spot market. Consider a typical U.S. power market with the PoolCo, the procedures for the wind IPP to sell its electricity are:

1) Bid in the day-ahead (DA) market for both the quantity and price of each hour for the next day
2) Be informed of the DA schedule, taking the DA locational marginal pricing (clearing LMPs)
3) In the real-time (RT) balancing market, get paid DA LMPs for DA scheduled generation
4) Get paid at RT LMPs for any generation that exceeds the day-ahead scheduled quantities, while will pay for generation deviations below the scheduled quantities.

3.4.1 Nash-Cournot Equilibrium in the Day-Ahead Forward Market

In the day-ahead market, assume all GENCOs are participating and bidding based on their own profit maximization, the DA clearing price, a.k.a the DA LMP will be decided based on the equilibrium of the supply curve and the demand forecast, therefore, the amount get dispatched in the DA market will be decided on the aggregation of all biddings from the GENCOs.

We consider a simplified case, when there are only two GENCOs in the market, one is the wind project, and the other one is a traditional power plant, their dispatched amount is q_1 and q_2. Assume the demand is a linear function of the total supply amount, then $p = \alpha - \beta \cdot (q_1 + q_2)$. The market follows a Cournot duopoly competition. The equilibrium will be reached when the two players follow their own profit maximization strategy.

For the wind project, since the variable cost can be assumed to be a small constant, the hourly bidding strategy can be expressed as:

$$max\, \Pi_1 = [\alpha - \beta(q_1 + q_2)] \cdot q_1 - C \tag{3-1}$$

$$s.t.$$

$$0 \le q_1 \le Q_1$$

Where $q_1$is the decision variable, and Q_1 represents the forecast mean of the generation amount for the certain hour. We follow the ISO/RTOs' rules that wind project cannot bid more than the forecasted mean the DA market.

Similarly, for the traditional power plant, the problem is also to maximize its profit, only difference is that it has a generation cost, which usually can be assumed as a linear function to the generation amount $\gamma \cdot q_2$. Therefore, the problem can be written as:

$$max\, \Pi_2 = [\alpha - \beta(q_1 + q_2)] \cdot q_2 - \gamma \cdot q_2 \tag{3-2}$$

$$\mathrm{s.t.}$$

$$0 \le q_2 \le Q_2$$

Here Q_2 represents the possible maximum generation capacity of the plant, it can chose to bid up to that amount in the DA market. Solving the problem for the two players, we can have some observations.

With individual optimization models built, we can combine the two problems, and solve the equilibrium for the market. The nonlinear program can be transferred into a nonlinear complementarity problem via its Karush-Kuhn-Tucker (KKT) conditions (Gabriel, Kiet, and Zhuang 2005). Therefore, we use complementarity method to solve this problem after proving its optimality sufficient by KKT conditions.

Let u_{11} and u_{12} be the Lagrangian multipliers for problem (3-1) constraints, and u_{21} and u_{22} for problem (3-2) .Then KKT conditions for the two problems, can be written as (Gabriel, Kiet, and Zhuang 2005):

$$2\beta q_1 + \beta q_2 - \alpha - u_{11} + u_{12} = 0 \tag{3-3}$$

$$0 \leq u_{11} \perp q_1 \geq 0$$

$$0 \leq u_{12} \perp Q_1 - q_1 \geq 0$$

$$2\beta q_2 + \beta q_1 - \alpha + \gamma - u_{21} + u_{22} = 0 \tag{3-4}$$

$$0 \leq u_{21} \perp q_2 \geq 0$$

$$0 \leq u_{22} \perp Q_2 - q_2 \geq 0$$

These two problems can be combined and improved as one Non-linear Complementary Problem (NCP):

$$0 \leq \begin{pmatrix} q_1 \\ u_{11} \\ u_{12} \\ q_2 \\ u_{21} \\ u_{22} \end{pmatrix} \perp G \begin{pmatrix} q_1 \\ u_{11} \\ u_{12} \\ q_2 \\ u_{21} \\ u_{22} \end{pmatrix} = \begin{pmatrix} 2\beta q_1 + \beta q_2 - \alpha - u_{11} + u_{12} \\ q_1 \\ Q_1 - q_1 \\ 2\beta q_2 + \beta q_1 - \alpha + \gamma - u_{21} + u_{22} \\ q_2 \\ Q_2 - q_2 \end{pmatrix} \geq 0 \tag{3-5}$$

Solving the problem by assuming different parameters for Q_1, Q_2, α, β, and γ, we can get the solutions for different situations and sensitivity analysis:

Table 3-1 Solution for NCP model and Sensitivity Analysis

Q1	***Q2***	**α**	**β**	**γ**	**Dispatched Amount for Wind Project**	**Dispatched Amount for Traditional Plant**	**Total Demand Met**	**DA Clearing Price**	**Cost for Traditional Plant2**	**Profit for Wind Project**	**Profit for Traditional Plant**
15	500	250	0.2	100	**15**	**367.5**	383	**174**	36750	2603	27011
50	500	250	0.2	100	**50**	**350**	400	**170**	35000	8500	24500
70	500	250	0.2	100	**70**	**340**	410	**168**	34000	11760	23120
110	500	250	0.2	100	**110**	**320**	430	**164**	32000	18040	20480
50	500	250	0.2	**50**	50	**475**	525	145	23750	7250	45125
50	500	250	0.2	**100**	50	**350**	400	170	35000	8500	24500
50	500	250	0.2	**150**	50	**225**	275	195	33750	9750	10125
50	500	**200**	0.2	100	50	**225**	275	145	22500	7250	10125
50	500	**250**	0.2	100	50	**350**	400	170	35000	8500	24500
50	500	**300**	0.2	100	50	**475**	525	195	47500	9750	45125

From the simple numerical solution, and the sensitivity analysis, we can observe that the wind project will always be dispatched to the upper bound that it is allowed to bid, due to its zero cost for power generation.

The sensitivity analysis checks the impact of the penetration level to the market, which is defined as following:

$$Penetration\ Level = \frac{Electricity\ from\ Wind\ Resouces}{Total\ Electricity}$$

We change the penetration level from the range of $\left(\frac{15}{515}, \frac{110}{610}\right) = (2.9\%, 18\%)$, from low level to high level of penetration. The higher the penetration level is, the less power the traditional plant will be dispatched, and the clearing price for the day-ahead market will be reduced accordingly.

The influence of the wind project to the existing market can be illustrated through the following Figure 3-5, where the power market is relaxed to a more general situation which include all different kinds of power plants. With additional power resources from wind, which has very low generation cost, all the existing supply curve (dotted curve) will be moved towards right (solid curve), which means some higher-cost power plant will lose some demand accordingly. The supply-demand equilibrium will be changed, the price will decrease, and the amount will increase.

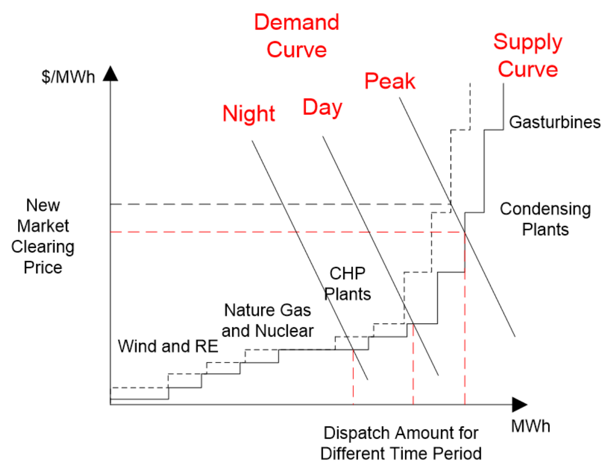


Figure 3-5 New Balance of Supply and Demand for the Power Market with Wind Resource. Adapted from (Ackermann 2012)

The change of the demand curve can be regarded as demand for different time period during the day. Since the power generated by the wind project and other intermittent renewables are always first dispatched, the change of the market demand will only affect the generation dispatch of the traditional plants. However, the market clearing price is changed accordingly, which will influence the revenue for the wind project.

Another important observation is that no matter how much the wind IPPs bid in the market, all the bidding amount will be dispatched. This phenomenon can be easily explained as follows: since the marginal cost of wind project can be regarded as zero, the wind IPPs will always bid at zero to maximize their profit, while all other GENCOs are bidding at their marginal cost, which are larger than zero. With a relatively low penetration of wind, the demand will be firstly met by wind, and then other resources, according to the merit-order. In the end, the market clearing price will be strictly positive, and all electricity generated from wind resource will be dispatched.

3.4.2 Revenue Optimization in the Real-Time Balancing Market

After all the bidding amount and the DA clearing price declared in the Day-Ahead forward market, all GENCOs are delivering their generation and realizing their profit in the Real-Time balancing market. If there is an imbalance between the generation and the real demand, ISO/RTOs will search for a new equilibrium based on the real-time demand signals and the day-ahead supply curve. Meanwhile, GENCOs will keep eyes on their actual generation situations and communicate with ISO/RTOs through amount and price signals. A Real-Time Price will be declared at a 5-min interval[1] based on the updated balance, and for GENCOs, the imbalance between the real-time delivery and the day-ahead dispatch schedule will be settled based on the RT price at an hourly basis.

With this procedure, the only decision the wind IPP should make is the generation amount to bid in the DA market Q_{DA} for every hour. In the traditional bidding strategies, profitability remains the prior objective. Advances have been achieved in the literatures proposing methodologies aiming to improve the expected profit. Since the fundamental problems wind IPPs are facing is the uncontrollable and unpredictability of wind resource, over the last decades numerous researches have been proposed in the meteorology and physical domain focused on how to better forecast the available wind resource (Wu and Hong 2007, Costa et al. 2008). While forecasting still will never give perfect results, especially over a longer time interval (e.g. daily), another direction is to mathematically design the strategy considering different market mechanisms through stochastic optimization frameworks (Matevosyan and Soder 2006, Rahimiyan, Morales, and Conejo 2011). The fundamental concept of this framework is to treat the uncertainty of the wind resource by considering possible scenarios (Bathurst, Weatherill, and Strbac 2002) or sampling from the probability distributions (Pinson, Chevallier, and Kariniotakis 2007). In this research, the idea is followed, and the stochastic optimization model is studied further to be integrated with another evaluation metric measuring the project revenue risks.

Different with traditional power generators, the variability and uncontrollability of the wind resource, together with the volatile electricity price, could cause a high volatility for the project future revenue stream. Sometimes the variance could be very high when the wind is not blowing

[1] Typical update interval are 5 minutes in US ISO/RTOs. There are also 10 or 20 minutes in other areas.

or there is a sudden gust causing the system to shut down. If the project is simply following the strategy to maximize the expected profit, it could be subject to an extensive loss for some events with low probability. As a matter of fact, the potential volatility of the cash flow has become one of the key problems preventing wind projects to participate in the merchandise wholesale market. A specific mechanism for project risk management should be incorporated when planning the offtakes. Therefore, another important metric of evaluating the offtake strategy for wind projects is the stability of the future revenue. The control of the revenue risk is a guarantee for a stable future revenue stream thus can largely increase the possibilities of the projects' success.

There are limited literatures measuring risks associated with short-term offtake of wind projects. Galloway followed the classic risk assessment method, the mean variance, and specifically combine it with the use of utility functions (Galloway et al. 2006). Morales and Conejo et al. proposed the conditional value at risk (CVaR) due to its good mathematical properties when incorporated with a linear programming (Morales, Conejo, and Pérez-Ruiz 2010). CVaR, as we discussed in the last chapter, has favorable characteristics especially when it is applied to the non-normal (or non-log normal) parameters (Rockafellar and Uryasev 2000). In this paper, we will follow the latter approach and apply the CVaR measuring the hourly revenue risk.

We now build the optimization model for wind IPP with the revenue and CVaR calculated on an hourly bases. Since the decision making is made in a stochastic environment, the objective is to maximize the expected value of the hourly revenues, and we add a constraint of revenue risk, measured using CVaR. Meanwhile, the bidding amount cannot exceed the expected generation amount. Hence, the problem of optimizing bidding strategy can be written as:

$$max\, E[\, R(Q_{DA}, Q_{RT}, P_{DA}, P_{RT})] \tag{3-6}$$

$$s.t.$$

$$\phi_{\beta}(Q_{DA}) \leq w$$

$$0 \leq Q_{DA} \leq E[Q_{RT}]$$

Where $R(Q_{DA}, Q_{RT}, P_{DA}, P_{RT})$ is the hourly return, with Q_{DA} as the decision variable, $\phi_\beta(Q_{DA})$ is the β-level CVaR for Q_{DA}, and w is the tolerance level for the risk.

It is proved by (Krokhmal, Palmquist, and Uryasev 2002) that this optimization problem have the equivalent formulations to the following problem, if the $R(Q_{DA}, Q_{RT}, P_{DA}, P_{RT})$ is concave, and $\phi_\beta(Q_{DA})$ and the set Q_{DA} are both convex:

$$min\, \phi_\beta(Q_{DA}) - \mu E[\, R(Q_{DA}, Q_{RT}, P_{DA}, P_{RT})] \tag{3-7}$$

$$s.t.$$

$$0 \le Q_{DA} \le E[Q_{RT}]$$

As discussed in the last session for the two-settlement market, no matter how much the wind IPP bid in the DA and the RT market can be totally dispatched. And the only decision the wind IPP should make is the generation amount to bid in the DA market Q_{DA} for every hour, whatever is the imbalance of the actual generation will be settled in the RT market, the hourly revenue $R(Q_{DA}, Q_{RT}, P_{DA}, P_{RT})$ can be written as:

$$\begin{aligned} Hourly\ Revenue &= P_{DA} \cdot Q_{DA} + P_{RT} \cdot (Q_{RT} - Q_{DA}) \\ &= P_{DA} \cdot Q_{DA} + (P_{DA} + \Delta P) \cdot (Q_{RT} - Q_{DA}) \\ &= P_{DA} \cdot Q_{DA} + P_{DA} \cdot Q_{RT} - P_{DA} \cdot Q_{DA} + \Delta P \cdot (Q_{RT} - Q_{DA}) \\ &= P_{DA} \cdot Q_{RT} + \Delta P \cdot \Delta Q \end{aligned} \tag{3-8}$$

Where:

P_{DA} − Day Ahead Clearing Price

Q_{DA} − Day Ahead Bidding Amount, Decision Variable

P_{RT} − Real Time Clearing Price

Q_{RT} − Real Time Generation Amount

ΔP − Difference between Real Time Clearing Price and Day Ahead Clearing Price

ΔQ − Difference between Real Time Generation and Day Ahead Bidding Amount

Usually, the Day-ahead market price is decided by the market equilibrium, and not influenced by each GENCO, hence P_{DA} and Q_{RT} can be regarded as independent. Meanwhile, the difference of the market price are based on the market situation, while the forecasting error of the power generation is only related to individual power producer's judgment and natural resource turbulence, hence ΔP and ΔQ can also be assumed to be independent. The expected value for the hourly revenue for the wind project is:

$$E[\,R(Q_{DA}, Q_{RT}, P_{DA}, P_{RT})] = E[P_{DA}] \cdot E[Q_{RT}] + E[\Delta P] \cdot E[\Delta Q]$$

On the other hand, the CVaR risk function $\phi_\beta(Q_{DA})$, by definition, measures the conditional expectation of the hourly loss (negative revenue) associated with Q_{DA} relative to that loss being $\alpha_\beta(Q_{DA})$ or larger. Therefore it can be written as:

$$\phi_\beta(Q_{DA}) = (1-\beta)^{-1} \times \tag{3-9}$$

$$\iiint\limits_{-R(Q_{DA},Q_{RT},P_{DA},P_{RT}) \geq \alpha_\beta(Q_{DA})} -R(Q_{DA}, Q_{RT}, P_{DA}, P_{RT}) p(Q_{RT}, P_{DA}, P_{RT}) dQ_{RT} dP_{DA} dP_{RT}$$

Where $\alpha_\beta(x) = min(\alpha \in \mathbb{R}: \Psi(x,\alpha) \geq \beta)$, which is usually referred to as the Value-at-Risk (VaR), defined as the left endpoint of the nonempty interval consisting of the values α such that $\Psi(x,\alpha) = \beta$. With $R(Q_{DA}, Q_{RT}, P_{DA}, P_{RT}) = P_{DA} \cdot Q_{DA} + P_{RT} \cdot (Q_{RT} - Q_{DA})$, then

$$\phi_\beta(Q_{DA}) \tag{3-10}$$

$$= \iiint\limits_{-R(Q_{DA},Q_{RT},P_{DA},P_{RT}) \geq \alpha_\beta(Q_{DA})} [-P_{DA} \cdot Q_{DA} - P_{RT} \cdot Q_{RT} + P_{RT} \cdot Q_{DA}]$$

$$\cdot\, p(Q_{RT}, P_{DA}, P_{RT}) dQ_{RT} dP_{DA} dP_{RT}$$

The bidding strategy is related to the exogenous parameters of the market and the wind resource. If the parameters are deterministic, the bidding strategy of every hour can be easily solved. If the parameters are stochastic, then the bidding strategy can be solved through sampling multiple times from the distribution or historical data.

3.4.3 Model Solvability

In order to deal with the troublesome mathematical properties of the β-CVaR, (Rockafellar and Uryasev 2000) proposed a methodology by defining a simpler expression $F_\beta(x, \alpha)$ with its convexity in the variable α, and it is proved later by (Krokhmal, Palmquist, and Uryasev 2002) that instead of determining a vector x that yields the minimization for the combination of β-CVaR and the expected profit, one can equivalently minimize the combination of $F_\beta(x, \alpha)$ and the expected profit.

Applying this methodology, we define the *F* functions of the CVaR problems as follows:

$$F_\beta(Q_{DA}, \alpha) = \alpha + (1-\beta)^{-1} \tag{3-11}$$

$$\times \iiint\limits_{Q_{RT}, P_{RT}, P_{DA} \in \mathbb{R}} [-P_{DA} \cdot Q_{DA} - P_{RT} \cdot Q_{RT} + P_{RT} \cdot Q_{DA} - \alpha]^+ \cdot p(Q_{RT}, P_{DA}, P_{RT}) dQ_{RT} dP_{DA} dP_{RT}$$

Where

$$[t]^+ = \begin{cases} t & when\ t > 0, \\ 0 & when\ t \le 0. \end{cases}$$

In the problem (4-21), if the parameters of Q_{RT}, P_{DA}, and P_{RT} are known as deterministic, then $F_\beta(Q_{DA}, \alpha)$ is convex and continuously differentiable as a function of α, hence the bidding strategy Q_{DA} can be solved directly by taking derivative of α and let it to be zero. However, there is no chance the parameters are deterministic when the bidding is made, then some sampling process should be taken in terms of each parameters based on their known distributions, or from historic data. In this problem, the sampling process will generate three series of vectors $Q_{RTk}, P_{DAk}, P_{RTk}, (k = 1, \cdots M)$ respectively from the distribution of actual electricity generation, day-ahead market price, and real-time market price, then the corresponding approximation to $F_{\beta}(Q_{DA}, \alpha)$ is:

$$\widetilde{F_{\beta}}(Q_{DA}, \alpha) = \alpha + \frac{1}{M(1-\beta)} \times \sum_{k=1}^{M} [-P_{DAk} \cdot Q_{DA} - P_{RTk} \cdot Q_{RTk} + P_{RTk} \cdot Q_{DA} - \alpha]^{+} \quad (3\text{-}12)$$

Although this expression is not differentiable to α, it is convex and piecewise linear with respect to α. Hence it can readily be minimized, either by line search techniques or by representation in terms of an elementary linear programming problem (Rockafellar and Uryasev 2000).

With this formulation written, the objective function of the original problem of (3-7) can then be expressed as:

$$min\, \alpha + \frac{1}{M(1-\beta)} \times \sum_{k=1}^{M} [-P_{DAk} \cdot Q_{DA} - P_{RTk} \cdot Q_{RTk} + P_{RTk} \cdot Q_{DA} - \alpha]^{+} + \frac{\mu}{M} \cdot [\sum_{k=1}^{M} (P_{RTk} - P_{DAk}) \cdot Q_{DA}] - \mu E[(P_{RT} \cdot Q_{RT})] \quad (3\text{-}13)$$

We further define another series of auxiliary real variables, $u_k, k = 1, \ldots, M$, to replace the maximization function $[t]^{+}$, and add corresponding constraints. Therefore, the problem of (3-7) is equivalent to the following linear expression:

$$min\, \alpha + \frac{1}{M(1-\beta)} \times \sum_{k=1}^{M} u_k + \frac{\mu}{M} \cdot [\sum_{k=1}^{M} (P_{RTk} - P_{DAk}) \cdot Q_{DA}] - \mu E[(P_{RT} \cdot Q_{RT})] \quad (3\text{-}14)$$

$$s.t.$$

$$(P_{DAk} - P_{RTk}) \cdot Q_{DA} + \alpha + P_{RTk} \cdot Q_{RTk} + u_k \geq 0, k = 1, \ldots, M$$

$$u_k \geq 0, k = 1, \ldots, M$$

$$0 \leq Q_{DA} \leq E[Q_{RT}]$$

Where Q_{DA} and α are decision variables, and P_{RTk}, P_{DAk}, and Q_{RT} are all stochastic variables.

With all the above mathematical techniques, the complicated stochastic problem is translated into a linear programming. Although the problem size depends on the specific M, the problem formulation is readily solvable using commercially available software.

3.5 <u>Case Study for Cape Wind Project</u>

3.5.1 <u>Overview of Cape Wind Project</u>

Cape Wind project, proposed on the Outer Continental Shelf (OCS) offshore, Massachusetts, is the first offshore wind project that has been approved in the U.S. coastal waters. The project area is located in Federal waters between Cape Cod, Martha's Vineyard, and Nantucket Island (Figure 3-6). As an IPP, the project developer Cape Wind Associates, LLC (CWA) plans to construct and operate 130, 3.6 megawatt (MW) wind turbine generators, each with a maximum blade height of 440 feet (80m), on Horseshoe Shoal in Nantucket Sound (Figure 3-7). The facility's total nameplate capacity will be 468 MWs, and with an average anticipated output of 183 MW, it will supply up to 75% of the electricity needs of Cape Cod and the Islands of Martha's Vineyard and Nantucket.

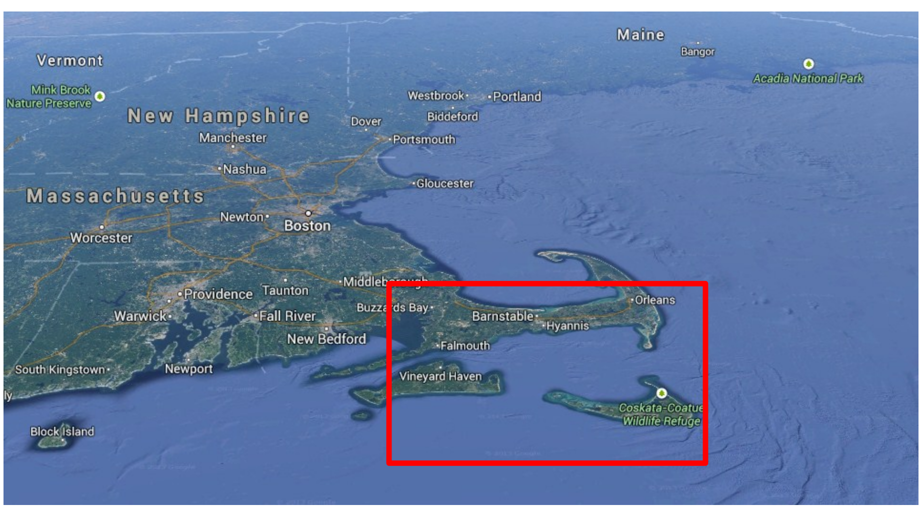


Figure 3-6 Cape Wind Offshore project. Source: Google Map.

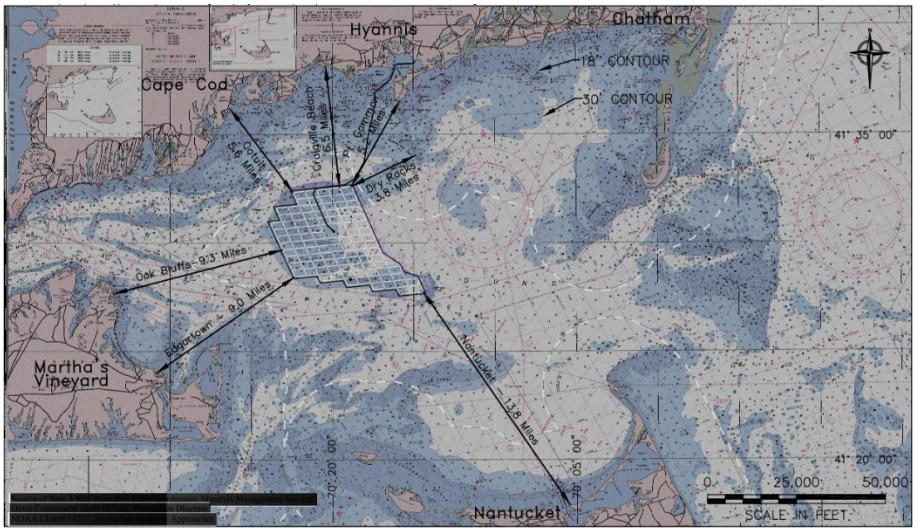


Figure 3-7 Location and Turbine Array for Cape Wind Energy Project. Source: BOEM.

The Cape Wind project is now undergoing the project financing phase, with two PPA contract already signed and approved, covering 77.5% of the total project capacity. Meanwhile, the remaining part of the project, 22.5%, will be sold through the spot market which is in the operation area of New England ISO. The time frame of the project is shown in the Figure 3-8.

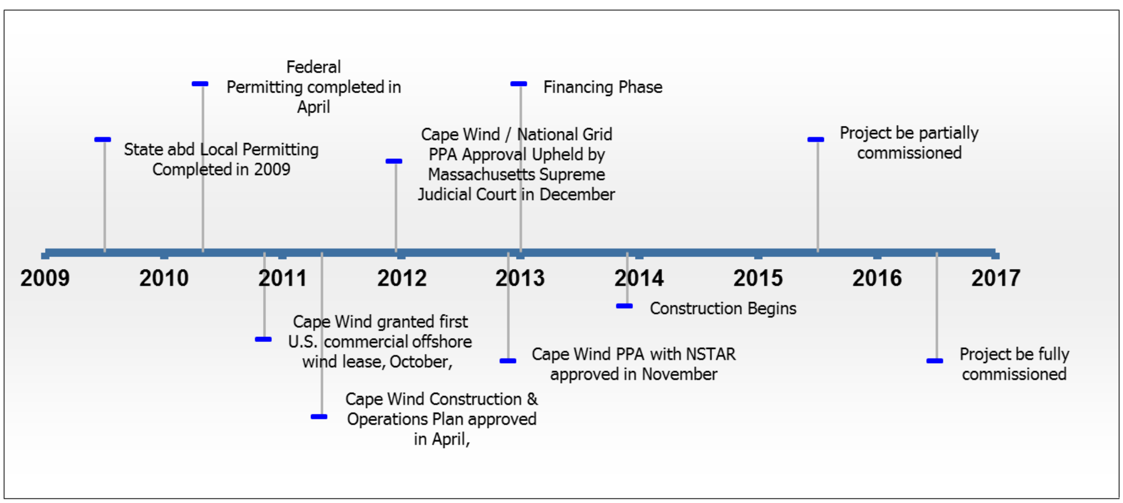


Figure 3-8 Timeline for Cape Wind Project

3.5.2 <u>Data Collection of Cape Wind Project</u>

Out-of-sample analysis, which essentially uses one data set to derive decisions and another data set to test the efficaciousness of the decision on actual operation, is going to be the method we use for the case study. For the Cape Wind project, the data for year 2009 to 2012 are set as the sample, and the decisions made from those data are applied for year 2013 actual data to test the performance. Specifically, the following data sources are identified:

1. Wind resource for the project location:

There is a meteorology station located very close to the project site. Historical and real-time data for wind speed and wind direction is available from the National Data Buoy Center online database (NOAA 2013), from March 2009 until present, at a 15-min interval. The data is captured by a buoy as shown in the Figure 3-9 from the National Oceanic and Atmospheric Administration (NOAA) system. Since the buoy is at the sea level, while the wind turbine for the project is at the height of 80m, wind speed will be modified according to the vertical wind profile reviewed in the Chapter 2. As also reviewed in the literatures, the wind speed doesn't fluctuate violently in a long-term time frame, hence the data from more than four years will be sufficient to estimate the monthly wind resource distribution.

Figure 3-9 NOAA Buoy Station 44020 at Nantucket Sound (NOAA 2013).

Due to the seasonality at the long-term scale and turbulence at the short-term scale for wind data, detailed statistic regression procedure are designed. Specifically, for each hour, a window for plus and minus one hour, and plus and minus fifteen days of each of the three years is applied to regret the wind speed Weibull distribution,

2. Technical Data for the Wind Turbine

This project is going to build 130 wind turbines that are manufactured by Siemens, each with 3.6 megawatt (MW) nameplate capacity. All the technical specifications for the turbine SWT-3.6-107 are available from Siemen's brochure. In particular, the most important information are listed in Table 3-2:

Table 3-2 Specifications for Siemens Wind Turbine SWT-3.6-107. Data source: (Siemens 2011)

Hub Height	*80 m*	**Nominal Power**	*3,600 kW*
Rotor Diameter	*107 m*	**Voltage**	*690 V*
Swept Area	*9000 m^2*	**Cut-in Speed**	*3-5 m/s*
Power Regulation	Pitch Regulation with Variable Speed	**Nominal Power**	*13-14 m/s*
Blade Length	*52 m*	**Cut-out Speed**	*25 m/s*

Meanwhile, the power curve is also provided as Figure 3-10, with which the power generation and corresponding efficiency from the wind turbines can be estimated more accurately.

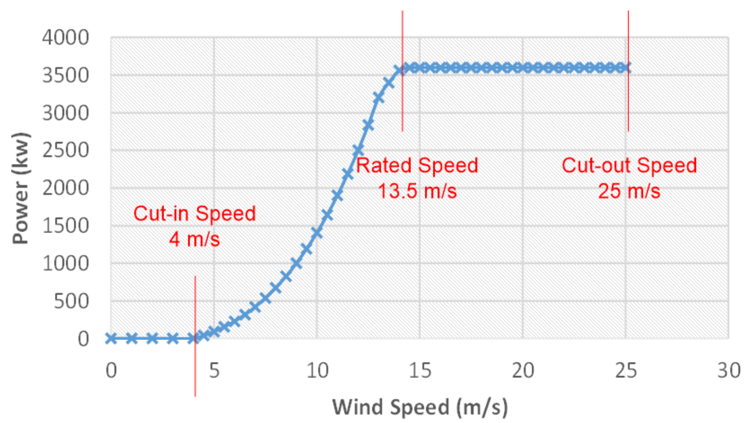


Figure 3-10 Power Curve for Wind Turbines of Cape Wind Project. Data source: (Siemens 2011).

3. Market information of electricity price

The project is located in the operation area of New England ISO, which is one of the nine major North American RTOs/ISOs, as discussed in section 3.2. As regulated by the Federal Energy Regulatory Commission (FERC), New England ISO keeps very detailed database records of the electricity market information on its website, such as the hourly DA and RT LMP, starting from March, 2003 (NEISO 2013). These information are critical in evaluating the market value of the project production, and will be treated as the input of the sampling seeds for real-time electricity price forecast. In the next two chapters, the market information will also be used as the base to estimate future electricity price, hence evaluate the project revenue stream.

Similarly, we use three years of DA/RT LMP data (year 2009-2012) to conduct the forecasting and apply it to the year 2013 for the verification. Specifically, a window for plus and minus one hour, and plus and minus fifteen days of each of the three years is applied to regret the normal distribution for the hourly DA and RT price.

With the above information available, this project is expected to be a perfect case study for this dissertation to analyze and compare throughout different strategies.

3.5.3 Sampling Seeds and Seasonal Trend

Regretted from the three-year data, the parameters for hourly wind speed, the DA price and RT price can be estimated respectively. The following three figures (Figure 3-11 to Figure 3-13) plot the regretted mean and standard deviation of these three parameters for each hour (altogether 8760 hours) in year 2013.

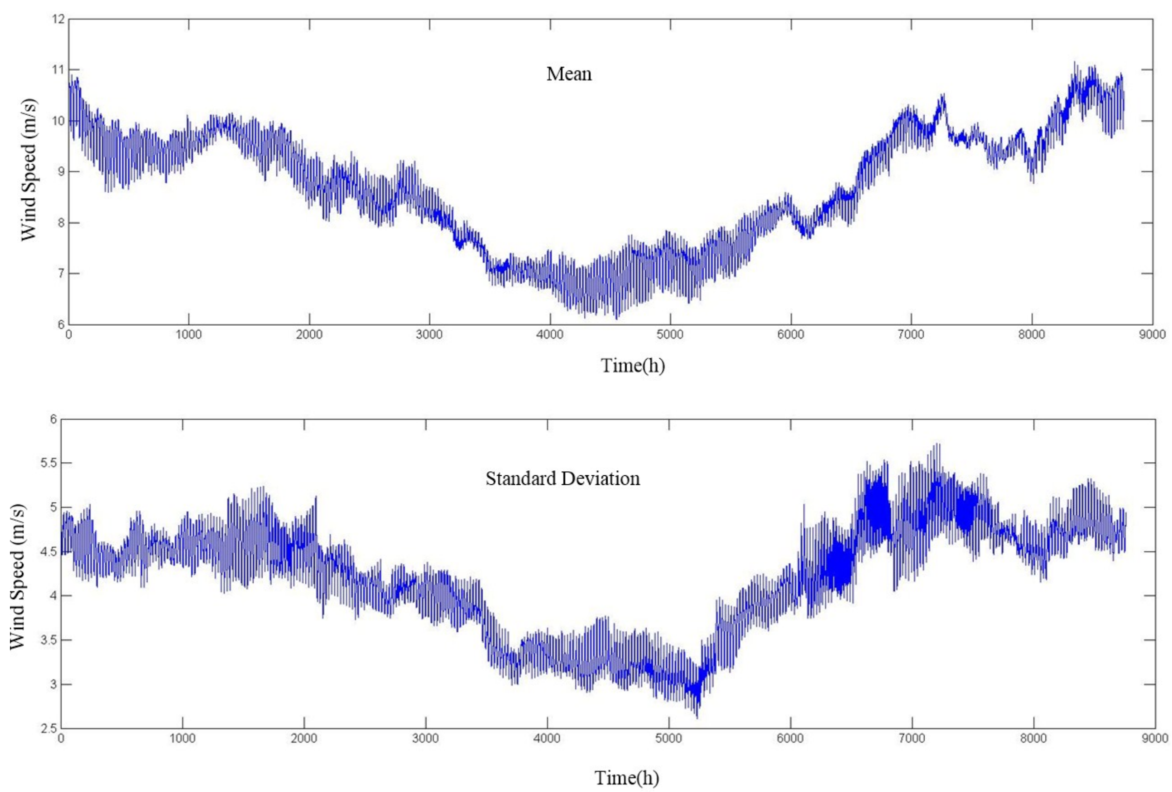


Figure 3-11 Regression Result for Hourly Wind Speed, year 2013

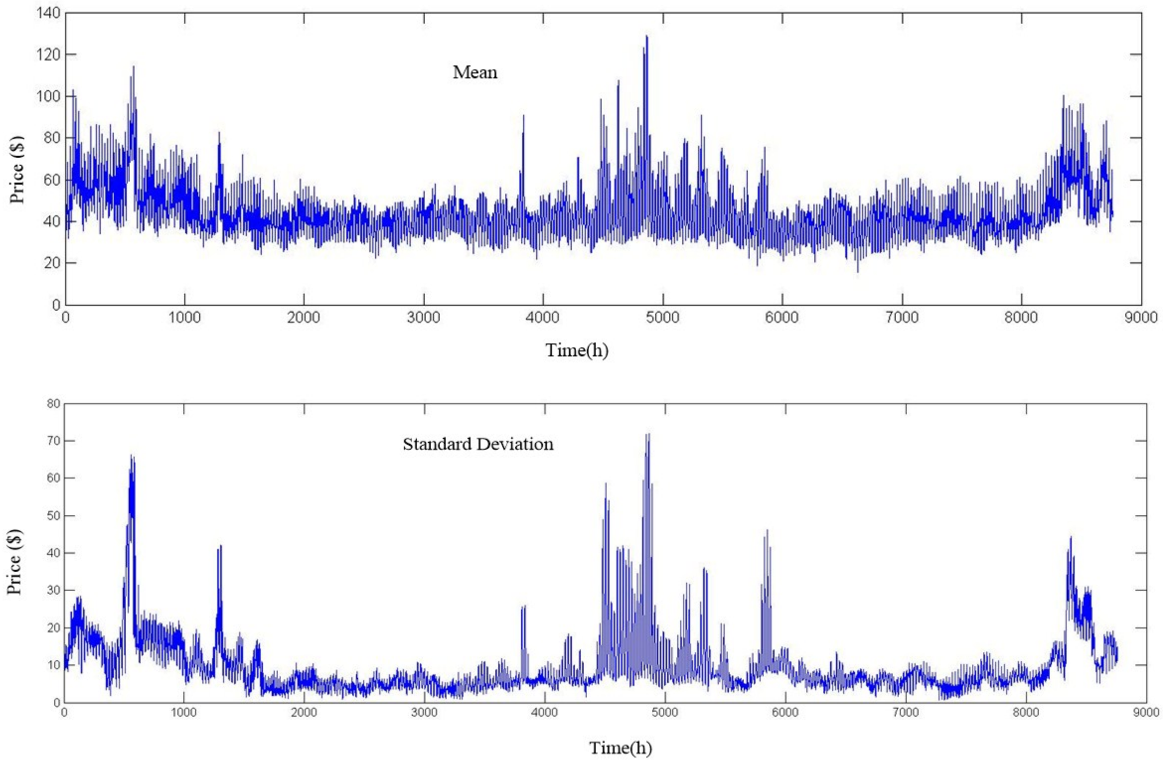


Figure 3-12 Regression Result for Hourly DA Electricity Price, year 2013

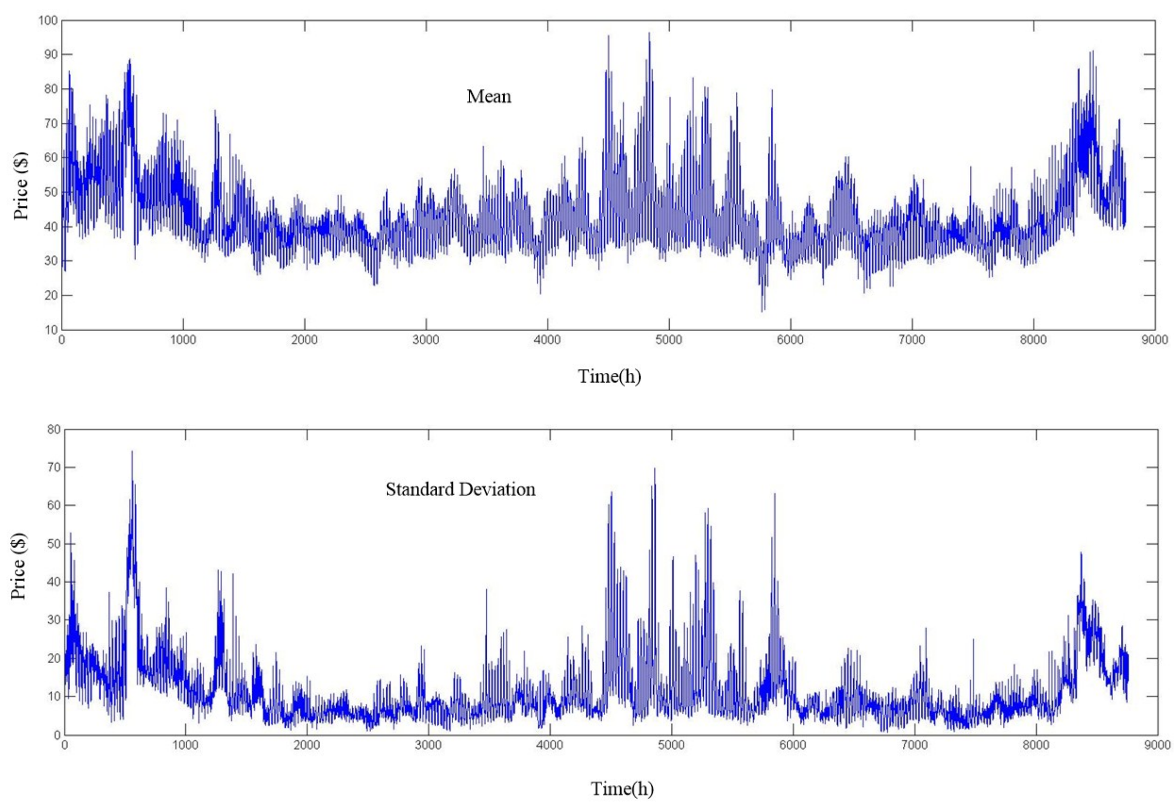


Figure 3-13 Regression Result for Hourly RT Electricity Price, year 2013

As shown in the result, all the three parameters have high volatility at the hourly base. The normalized standard deviation, defined as $\frac{Standard\ Deviation}{Mean}$, respectively range from 35%-65% (for wind speed), 8%-47% (for DA electricity price) and 10%-50% (for RT electricity price).

A strong seasonal trend can also be observed from the results, both for the means and standard deviations. While wind resource shows a larger various during fall and spring, and smaller volatility during winter and summer, the trend for electricity price is on the opposite direction. This phenomenon is helpful in eliminating some of the integrated volatilities. But due that the value of the profit $P_{DA} \cdot Q_{DA} + P_{RT} \cdot (Q_{RT} - Q_{DA})$ is dependent on the absolute value of the parameters, the trend of the electricity price still dominants. Hence it is expected that the project revenue cash flow will have higher uncertainties during summer and winter, and the bidding strategy will also be expected to show some related seasonal trend.

3.5.4 Bidding Strategy and Risk Attitude

One parameter in the model that is to be set associated with the risk is the weight $\mu = \frac{1-\lambda}{\lambda}, \lambda = [0,1]$ for the conflicted objectives. The smaller the λ, the larger the μ is, thus the more weights are allocated to the risk control, and the more risk averse the wind IPP is. Specifically for the first hour of Jan.1st, we run the model with λ changing from 0 to 1, with incremental step=0.001, the results are shown in Figure 3-14 and Figure 3-15.

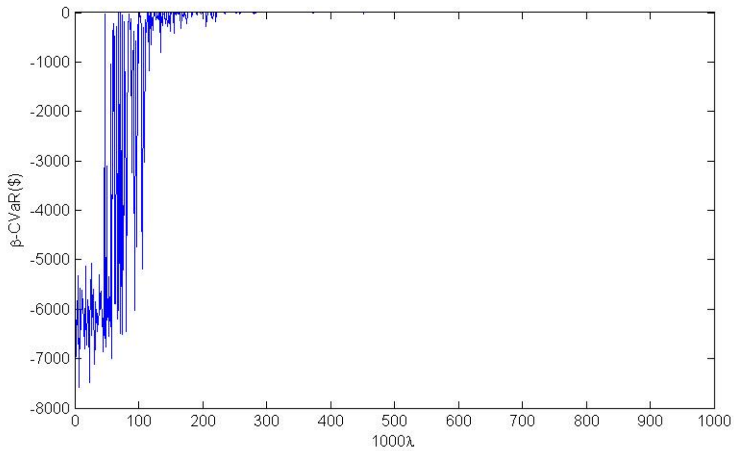


Figure 3-14 Hourly β-CVaR of Revenue with Different Weight (hour 1)

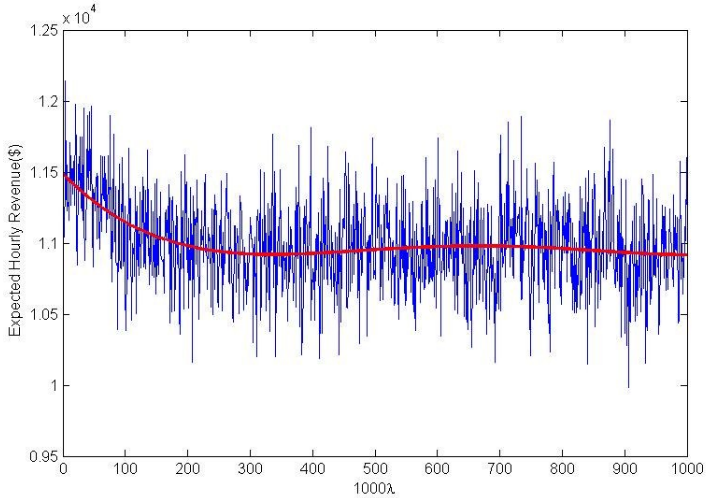


Figure 3-15 Expected Hourly Revenue with Different Weight (hour 1)

It can be observed that the expected hourly revenue of the project decreases when λ is getting larger, while maintain within a steady range when λ reaches around 0.2. Similarly, the hourly CVaR is increasing dramatically with λ, and stays as zero after λ is more than 0.2. Therefore, the inflection point $\lambda = 0.2$, making $\mu = 4$, could be regarded as a reasonable weight to balance the conflicted objectives. A detailed efficiency frontier can be derived with combination of the CVaR and profit at each μ.

Sampling from the three stochastic parameters, the linear programming (3-14) is applied to deal with the short-term offtake strategy for Cape Wind project for year 2013. The bidding amount for each hour is then solved. Meanwhile, different risk attitudes in terms of the confidence level β, are applied. The higher the β means the more risk averse the wind IPP is. For example, $\beta = 0.95$ means the wind IPP is trying to minimize the losses that is more than the 95% percentile, thus less risk is taken for the extreme cases.

The bidding strategies with different risk confidence levels β are shown in the Figure 3-16 - Figure 3-18. It is worth noticing that the bidding amount showing in the figure is for each wind turbine. Since we don't consider the wake effect between wind turbines, the hourly bidding amount for the whole project can be simply calculated by multiplying the number of facilities, 130.

According to the results, the seasonal trend is obvious that wind IPP is willing to bid more in the DA market during fall and spring, when the volatility of the trading environment is relatively low comparing with summer and winter, as discussed above.

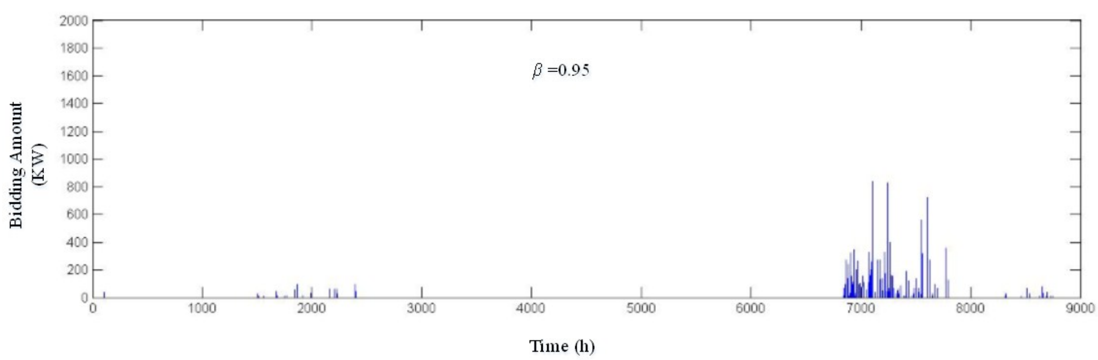


Figure 3-16 Hourly Bidding Strategy with $\beta = 0.95$, year 2013

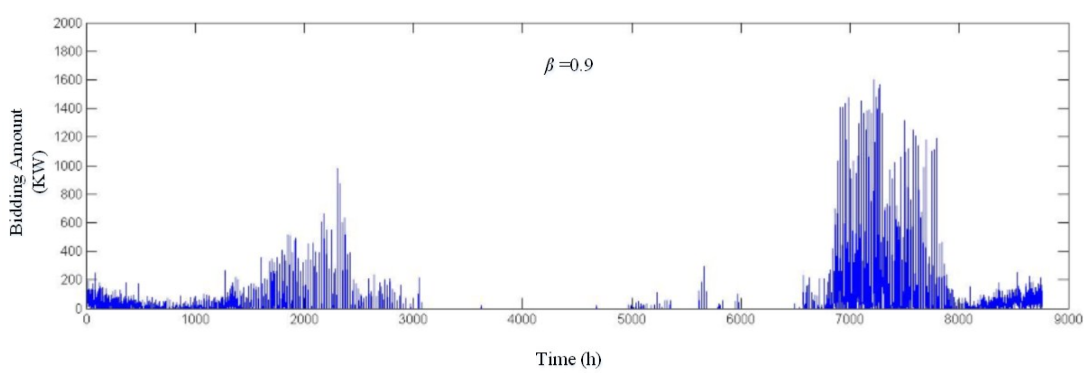


Figure 3-17 Hourly Bidding Strategy with $\beta = 0.9$, year 2013

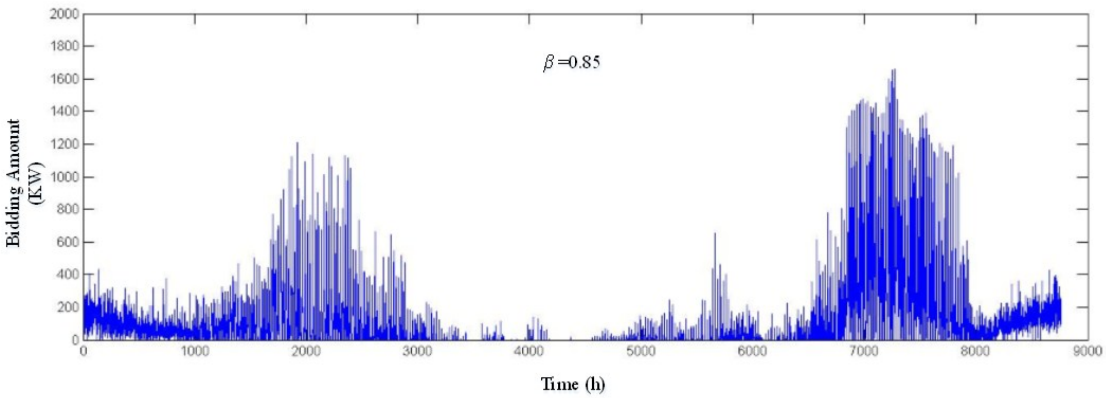


Figure 3-18 Hourly Bidding Strategy with $\beta = 0.85$, year 2013

It can also be observed that the more risk averse (higher confidence level β), the less the wind IPP is intended to bid in the DA market, and settle more of the offtake in the RT market. In order to verify this phenomenon, we now illustrate the relationship between the confidence level β, hourly revenue and cash flow risk CVaR. Specifically for the first hour of Jan.1st, we run the program by changing the β levels from 0.5 to 1. The corresponding bidding strategy, hourly revenue and hourly CVaR of the project can be calculated, as shown in Figure 3-19 and Figure 3-20.

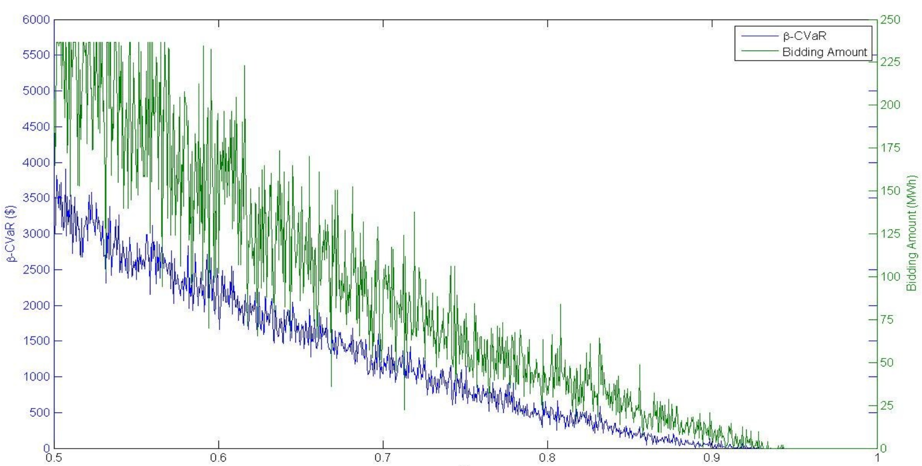


Figure 3-19 Bidding Amount and CVaR with Regard to Confidence Level β (hour 1)

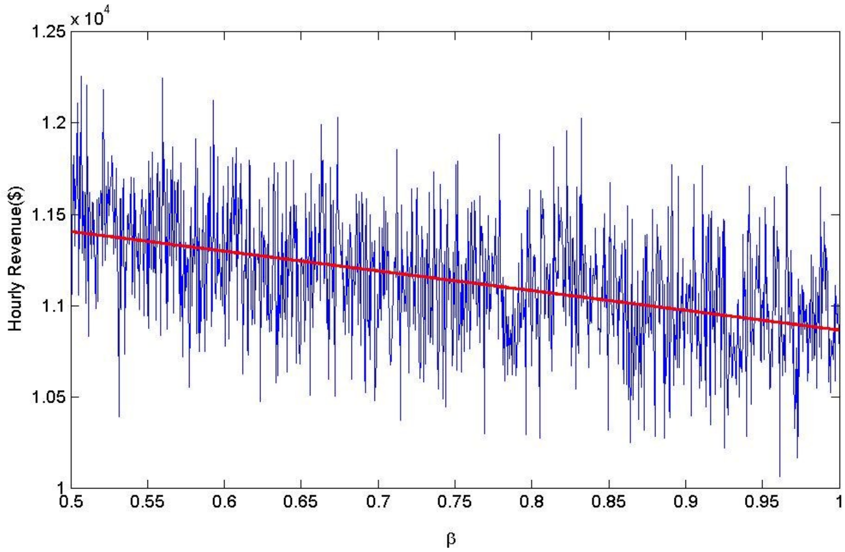


Figure 3-20 Hourly Revenue with Regard to Confidence Level β (hour 1)

With β increases from 0.5 to 1, the bidding amount of the project in the DA market decreases dramatically from the ceiling for the bidding to zero. The revenue risk is controlled more strictly, with the expected β-level-losses changing from around \$4,000 to zero, while the expected revenue is also decreasing accordingly, from around \$11,400 to \$10,900. This can be understood as a trade-off between the profit and the risks. Risk-taking IPPs tend to take the opportunity of the uncertainty, hoping to make money from the market volatility, while risk-averse IPPs are more willing to sacrifice the potential profit and control the possible losses.

3.5.5 Out-of-Sample Analysis —Performance Comparison

In this part, the performance of strategies will be discussed based on the application of model solutions (based on the year 2009-2012 data) on the actual market of year 2013 for the Cape Wind project. Specifically, we will consider the revenue flows, and some statistical inferences for risks to measure the performance of the strategy we proposed and compare with the other two traditional strategies and an ideal case:

1) Strategy S_1 (Proposed Strategy):

This is the strategy we proposed, and solved by the stochastic program we built. The weight μ is 4 and the Confidence Level β is set as 0.9 for the case study, while both of the parameters can be adjusted according to the risk attitude of the wind IPPs.

2) Strategy S_2 (Traditional):

The most traditional strategy for wind IPPs to bid in the DA market is to bid on the best hourly estimation of the next day electricity generation, which is usually at the 50th percentile of the generation estimation. The performance of this method is not based on optimized decision making but highly dependent on the accuracy of the wind speed forecast.

3) Strategy S_3 (Baseline):

Another commonly used strategy is to maximize the expected hourly revenue, combining the estimation for wind resource and DA and RT electricity prices. This strategy can be easily modeled as follows:

$$
\begin{gathered}
max\, E[\, R(Q_{DA}, Q_{RT}, P_{DA}, P_{RT})] \\
= max[\overline{P_{DA}} \cdot Q_{DA} + \overline{P_{RT}} \cdot (\overline{Q_{RT}} - Q_{DA})] \\
s.t. \\
0 \leq Q_{DA} \leq E[Q_{RT}]
\end{gathered} \tag{3-15}
$$

Where $\overline{P_{DA}}$, $\overline{P_{RT}}$, and $\overline{Q_{RT}}$ are respectively the expected mean for the three parameters. The result can be solved directly through linear programming.

4) Strategy S_4 (Ideal Case):

This is an ideal case where all parameters are known to the wind IPPs thus are deterministic when they are making the decisions. The problem is easily solved by plugging in the actual data as the estimation for parameters. However, this strategy is not possible to achieve since the forecast cannot be perfect, the solution is purely derived for comparison and illustration.

5) Comparison of Strategy Performances

With all four different strategies ready, we can conduct the out-of-sample analysis. The performances of each strategy are to be compared based on the actual revenue achieved, and the risks associated with the cash flow. The revenue cash flow for each strategy are shown in the Figure 3-21.

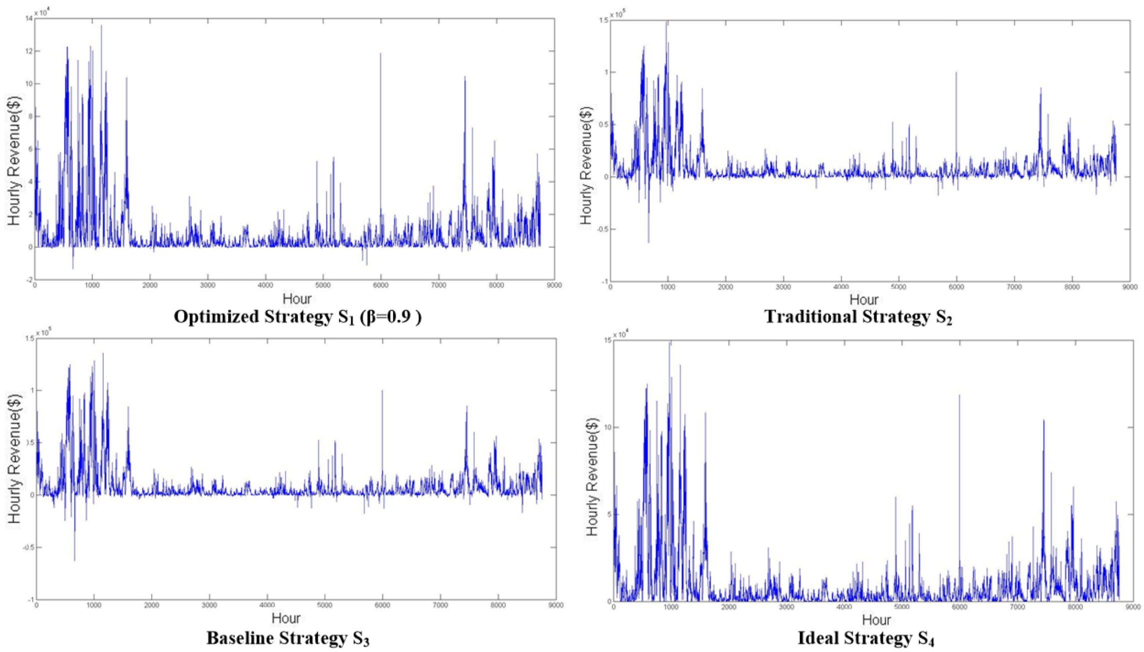


Figure 3-21 Comparison of Hourly Cash Flow for Each Strategy

It can be observed from the figures that the winter is the best time for wind projects to achieve profit, due to the abundant wind resource and high electricity value. However, winter is also the period when the cash flow has the highest volatility. The two traditional strategies, S_2 and S_3 both have highly negative hourly cash flow (losses), which can reach about -5×10^4dollars. This is a relatively severe problem for small IPPs. The proposed strategy S_1 effectively improves this situation, where there are very limited cash flow that are negative, and the biggest loss is controlled below -1×10^4 dollars. To this sense, the cash flow pattern of the proposed strategy $S_1$is the best match to the ideal case S_4.

Table 3-3 Out-of-Sample Analysis for Different Strategies

	Variance of Cash Flow	**Semi-variance of Cash Flow**	**0.05-percentile of Cash Flow**	**Mean of 0.05-percentile**	**Accumulated Annual Revenue**
Proposed Strategy S_1	1.83E+09	4.13E+07	0	-97	7.36E+07
Traditional Strategy S_2	1.86E+09	6.27E+07	-411	-2470	7.51E+07
Baseline Strategy S_3	1.87E+09	5.85E+07	-50	-1846	7.51E+07
Ideal Strategy S_4	2.00E+09	4.71E+07	0	0	8.06E+07

Some other results of the analysis are shown in the Table 3. The proposed strategy derives the least variance and semi-variance for the cash flow, which is the result from the CVaR control module of the model. Meanwhile, the left-side tale of the cash flow which represents the potential losses are of more interests than the general variances. Therefore, a 0.05 percentile and mean for that part is calculated for each strategy. The proposed strategy shows a dominant outperformance than the traditional strategies. Respectively, the mean of 0.05-percentile cash flow is increased by|(-97-(-2470))/(-2470)|=96%, and|(-97-(-1846))/(-1846)|=94.7%. However, as a trade-off, the proposed strategy also gets the least accumulated annual revenue, about (7.51-7.36)/7.51=2% less than the traditional two strategies.

3.6 Effects of Proposed Offtake Strategy on the Existing Market

The strategy we propose are specifically designed for wind IPPs to offtake their electricity generation in the market. It is expected to help the wind projects to better manage their resources, and participate in the power market in a more rational way. In the meantime, utilizing this strategy will also provide some benefits to the power market in terms of the electricity delivery stability, system reliability, and information use.

As we discussed, the wind project can basically be dispatched no matter how much they bid in the day-ahead market, with only one constraint as not exceeding the expected generation. In the traditional manners, wind IPPs are tend to bid as much as possible in the DA market, while have a high possibility not be able to deliver the promised generation. With the proposed strategy, the wind IPPs are tend to be more conservative, and push their decision making towards the RT market. The forecast accuracy can be largely improved during this period, and the bidding amount becomes more reliable. In other words, the strategy reduces the probability that the wind project will deviate too much from what it promises in the bidding. This is important for the system reliability especially with the increase penetration level of wind resource. And the other power producers and ISOs can also count on the wind IPPs decisions to adjust their hourly strategy, without worrying too much about the variability that wind will bring.

3.7 Conclusion

The offtake strategy proposed in this section helps wind IPPs make decision for hourly bidding based on estimation of future uncertain parameters including the wind speed, the DA electricity price and the RT electricity price. This approach considers the stochastic nature of these parameters, which is the key improvement of the two traditional methods which only consider the expected value. A stochastic program is built to solve the problem by incorporating conflicted objectives of maximizing the profit and minimizing the risks which is measured by a metric called Conditional Value-at-Risk (CVaR). Implementing the new strategy, the wind IPPs are expected to obtain a better balance between the profitability and the volatility of their revenue streams. The Cape Wind project in MA, the U.S. is discussed as the case study. With wind and electricity price data from year 2009 to 2012, the optimized offtake strategy for year 2013 is then solved. With a comprehensive out-of-sample analysis, the effectiveness of the new strategy is discussed and compared with traditional ones. Some other conclusions are duly drawn.

Chapter 4. Offtake Strategy for Wind Projects in the Bilateral PPA Relationship

4.1 __Introduction__

Bilateral contracts play a critical role in the electricity market as hedging tools against the volatile spot market price. While typical customized bilateral contracts are medium-term and are for less than 5 years (Anderson, Hu, and Winchester 2007), there is a type of long-term bilateral contract (usually with terms of 10 to 25 years) called Power Purchase Agreement (PPA) which is commonly utilized for renewable energy projects. As a matter of fact, by 2008 over 60% of all commercial solar projects are financed using PPA framework, the number keeps increasing (Thumann and Woodroof 2009). American Wind Energy Association (AWEA) reports that 85% of the wind power capacity installed in year 2012 by IPPs was contracted under long-term PPAs, and only 15% was sold on the short-term spot market (AWEA 2013b).

Especially for wind projects, as discussed in the last chapter, the uncertainties of the natural resources and the spot market construct a volatile revenue stream. Most wind energy projects developed by IPPs are not self-sustained, but dependent on the external support or regulatory incentives. Therefore, PPA is a more favorable way to offtake electricity productions since the buyer guarantees the project developer of a certain amount of long-term purchase, which makes the project more promised in the initialization phase. A well-designed bilateral PPA contract will help IPPs to secure the future revenue stream thus largely enhance the projects' feasibility and bankability for initial financing.

It is, however, a challenge to design and negotiate a PPA contract. In practice, there lacks a systematic method for project developers to analyze their negotiation position. Since renewable energy projects are typically deemed as risky and volatile to get initially financed, sometimes the project developers have to accept some onerous terms requested by power purchasers so as to sign off as much offtake as possible to get the project started (Umanoff 2008). Paradoxically, in the current negotiation and designing process of long-term PPA, the risks of the project revenue stream are rarely considered due to the difficulties of forecasting future exogenous factors. Instead, the typical approach for valuing a PPA is to estimate the projected annual cash flow based on the forecasted electricity price and cost, and then discount the expected future profits by the cost of capital of the investing firm. The project's feasibility is then evaluated by comparing the profit with the initial cost (Deng 1999). This so-called discounted cash flow (DCF) approach needs to be improved for wind projects, especially in the deregulated electricity industry because (1) it does not address the stochastic nature of the electricity price and the wind resource, which directly link to the volatility of the project future cash flow; and (2) it does not capture the seasonal pattern of the stochastic parameters, which fluctuate severely within a year. Once the pattern is captured, the generation capacity can be better utilized and the revenue and risks can be better balanced.

This chapter will review the current practice of typical PPA negotiations, and identify the pros and cons. Three different modified strategies are then proposed including incorporating stochastic programming, improving the settlement schedule, and balancing the revenue and risks, to help both parties to better understand their positions in the stochastic environment. The key of the contract design is the risks of the project future cash flow, measured by the Conditional Value-at-Risk (CVaR). Critical parameters in PPA, such as the electricity price, quantity, delivery penalty and outperformance reward will be determined by the stochastic programming with chance constraints related to the buyer's attitude of signing the contract. The performance of different PPA design strategies will be further discussed based on the case study of the offshore wind project Cape Wind with out-of-sample validations.

4.2 Literature Reviews for Current PPA Design and Negotiation

In the past times, PPA was a vehicle for utilities to purchase energy from each other in the vertically integrated power system (Kollins, Speer, and Cory 2010). For them, the PPA contract was regarded as a financial tool, a swap to hedge the risks from the electricity market, and is only different with forward contracts in the contract length. Therefore, one area with various literatures are to identify and manage the risks that are addressed by that type of PPA, such as electricity spot price volatility, network-forced outages, transmission congestion and load forecast errors (Gutiérrez-Alcaraz and Sheblé 2004, Dahlgren, Liu, and Lawarree 2003). The key problem of managing those PPAs is to balance the benefit and risks with a portfolio of contracts (Pearson 2011). The methodologies proposed include fuzzy set theory (Schmutz, Gnansounou, and Sarlos 2002), game theory (Ferrero, Shahidehpour, and Ramesh 1997), and stochastic optimization (Liu et al. 2000, Gabriel et al. 2006), etc.

Nowadays, due to the higher demand for developing renewable energies, more and more utilities are signing PPAs with independent renewable energy producers so as to meet state renewable portfolio standards (RPS). Moreover, PPA has become a more commercial variant that involves buyers other than utilities such as schools, government agencies, and business centers that are seeking green energies. As a result, those PPAs are more focusing on the physical delivery of the "green" electricity, and are regarded as performance-based contracts (Kim, Cohen, and Netessine 2007, Hansen 2006), where the payments are directly related to the actual delivery of the product, together with outperformance and penalty terms. Therefore, another area that is of more interest in the researches is the negotiation process of those PPAs (Anderson, Hu, and Winchester 2007). (Powell 1993) analyzed the contract process assuming that the generator decides on the price, and the buyer decides on the quantities. (Green 1999), on the contrary, assume that the seller and the buyer determine the contract quantities and contract prices respectively. Furthermore, an iterative negotiation procedure is simulated in (Khatib and Galiana 2007) assuming both parties have their own preference of benefit and risk measures.

The time frame of the bilateral relationship is also an important factor when both parties are evaluating the risks of the contract. Longer time horizon carry larger risks due to the future uncertainties from all different aspects (Anderson, Hu, and Winchester 2007), such as RE industry policies, new technology development, and market design renovation. The most common methodology to deal with the multiple time steps is to generate scenario trees for parameter forecasting (Høyland and Wallace 2001, Pflug 2001). For example, (Shrestha et al. 2005) defines a 256-scenario four-stage tree to model medium-term hydropower generation planning. (Carrión, Conejo, and Arroyo 2007) identifies a 72-period scenario tree and uses a scenario-reduction technique called fast-forward reduction algorithm to select a subset of scenarios to represent most scenarios.

For wind project, there are mainly two classes of PPAs, namely buyer-driven and seller-driven, based on the project size, location, and project delivery methods. The contract proposing, designing and delivering procedure varies from each other.

The U.S. DOE and the U.S. EPA both encourage wind projects and green power development through buyer-driven PPA relationships (Lund, Østergaard, and Stadler 2011). The well-known customer-sited PPA pattern has been utilized widely in the U.S. government agencies and many other institutions (EPA 2010, Shah 2011). In that relationship, a site owner intends to develop some in-house renewable energy, but they neither have the development capability, nor are eligible for the incentives such as tax credits. They sign a PPA with a renewable project developer, who is responsible for all the project financing, facility installing, and operation and maintenance, and only need to pay for the electricity generated through the project according to the price negotiated in the PPA. The project developer, usually owning the project, is able to get paid from the selling of the production, and benefit from the corresponding credits or accelerated depreciation (EPA 2013). This type of PPA is similar to the idea of Energy Management Project (EMP) or Energy Savings Performance Contract (ESPC) (Thumann and Woodroof 2009), where the buyers of the product/service shop around for the sellers based on their expected benefit, and the sellers evaluate the profit by calculating their Net Present Value (NPV) or Internal Rate of Return (IRR) (Newnan 2004), and give the quote. Those wind projects are usually small due to the limitation of the site and the electricity demand.

For larger-scale wind projects with capacities ranging from ten to even several hundred MW such as industrial offshore projects, the PPAs are driven by the project developer, who is usually also the seller of the product. In that type of projects, the developer starts with the project initiation, gets permits, contracts for the designers, manufacturers and other stakeholders. After the project has a mature plan, proposed schedule, and especially that the generation capacity has been determined, the project developer starts to settle their offtake strategies. Long-term PPA is the favored option, not only because the future revenue streams are secured, but also that the offtake can be prolonged to a monthly even yearly base so that the short-term volatility can be smoothened out. Therefore, the project developers usually try their best to lock as much as their offtake with PPAs, and the remaining capacity will be sold to the spot market. With these PPAs, the project’s future revenue and cash flow risks are the key concerns when the project developers propose the contract, and seek for buyers (Jenkins and Lim 1999). In practice, the PPA and project financing are conducted simultaneously, and the negotiation process could take long period of time even years. While only when the project is endorsed by a solid offtake plan, it is possible to get a sound financing package.

Although the long-term PPA has some obvious advantage over short-term offtake strategies, and it has been applied in the electricity market for a long period of time, it is still in the immature phase for the wind energy industry (Kollins, Speer, and Cory 2010). There still lacks a common framework to systematically design the contract terms and evaluate the benefits, given the high volatility of the electricity market and the wind power resources, as well as the uncertainties of the industry. In order to get the project financed, the developer is usually in an inferior position when designing the contract, as well as negotiating with the buyer. Although the future volatilities are expected to be lowered, PPA may still sacrifice a fair amount of the expected profit, together with some good opportunities associated with the uncertainties, which makes the PPA prices generally lower than the wholesale market electricity price (Wiser and Bolinger 2012). The typical viewpoint in the RE industry for current PPAs are that they under-evaluate the real value of those RE projects (AWEA 2013a).

4.3 Contribution and Boundaries

Addressing the discussed problems, the contribution of this section are threefold:

(1) Propose three improved strategies using stochastic programming to address the risks from both the volatile electricity market and the uncertain wind resource, with seasonal trend fully considered. Each strategy has unique framework to follow and can be solved through commercially available software package. With analytical solutions, the performance measure metric of the strategies are defined, and the effectiveness of all the strategies are analyzed and compared with the business-as-usual baseline strategy.

(2) Treat the PPA as performance-based contract, and quantitatively design the contract terms. The key contract terms that are essentially associated with the performance-based mechanism are the outperformance price, and underperformance penalty, which are interacting with the other contract terms. These two terms are not only considered, but also solved simultaneously through the optimization.

(3) Incorporate both parties' attitudes in the single model. All strategies are modeled from the project developer's perspective, while taking buyer's non-regret probability as chance constraint.

Therefore with the new methodologies, the contract design plays a role of benefit sharing and risk sharing.

Meanwhile, we make several assumptions and define the boundary of the problem discussed in this section as:

(1) Only one PPA contract is considered in the long-term offtake strategy. Although it is usually recommended for the wind IPP to diversify the contracts among different counter parties for credit risk reasons (Anderson, Hu, and Winchester 2007), we assume a single contract design in our problem. As for the problem of allocating the generation capacity between different buyers, the theory of portfolio management can be used to further develop the multiple contracts (Reilly and Brown 2011, Pearson 2011). This one-buyer contract can be regarded as the special case of identical buyers, or the weighted sum of the portfolio contracts.

(2) Detailed one-year contract terms are solved. For a long-term PPA, it is usually assumed that the wind and electricity price respectively follow similar patterns within one year, therefore, the only different term applied to different years is an escalation rate, which is used to deal with the annual inflation, as well as the long-term uncertainty. The decision for the escalation rate depends on different parties' estimation for future uncertainties such as the new policies or technology development. In this section, we only consider the contract for one year. The escalation rate can be discussed in the future researches using the methodology that is reviewed in the previous part, the scenario tree (Shrestha et al. 2005, Carrión, Conejo, and Arroyo 2007).

(3) Renewable Energy Credits (RECs) and other environment attributes are not considered. The environmental benefits associated with the renewable energy projects are another big topic with complicated problem settings such as carbon market, carbon trading scheme and market design problems. In detailed trading, the RECs can be regarded as a bi-product that the project generate and sold as unbundled, or in some contract the electricity and RECs are bundled as one price, depending on the negotiation for both parties, and is case sensitive. For the contract design, if the

RECs are considered, they can be treated similarly as the electricity, with a separate stochastic REC price. However, due to the unclear future of the REC market, and the relative low value, it is not considered in this study.

4.4 PPA Contract Design

Now we consider a contract where the project is selling all of its generation through, and the buyer is large enough to digest all the deliveries. At that case, there is no curtail requested from the demand side, and all the generations will be delivered to the buyer. Therefore, the key problem of the contract design is about how much the power is, and what the mechanisms are to share the profit and the risks.

We start with the simplest contract which is most common in the industry, and propose three different strategies to improve it. The improvement include bringing stochastic parameters in the model, and designing different settlement methods.

4.4.1 Deterministic Scenario: the Baseline Strategy S1

The deterministic decision making is the most straight forward strategy that wind IPPs could go for, and is commonly practiced in the industry. In this strategy, the unknown parameters are estimated through point estimation with statistics of historic data or forecasting. In specific, the future electricity generation is estimated by calculating the annual capacity factor of the project, and the electricity market price is estimated by the expected mean based on the historic market price.

For each year, there are three variables to be decided, the quantity, the price, and the outperformance price. The detailed model can be expressed as (4-1) to (4-3):

$$max\, E\left[\bar{P}\times\bar{Q}+\overline{P_O}\cdot max\left(\left(\sum_{j=1}^{12}Q_{RTj}-\bar{Q}\right),0\right)+\overline{P_{RT}}\cdot min\left(\left(\sum_{j=1}^{12}Q_{RTj}-\bar{Q}\right),0\right)\right] \tag{4-1}$$

Subject to

$$E\left[Cost_{Buyer}(PPA)\right]-E\left[Cost_{Buyer}(Market)\right]\le 0 \tag{4-2}$$

$$\bar{P}\ge\overline{P_O} \tag{4-3}$$

Where

$\bar{P}$ — Contract Price, \$/Mwh

$\bar{Q}$ — Contract Delivery Amount, Mwh

$\overline{P_O}$ — Contract Outperformance Price, \$/Mwh

Q_{RTj} — Actual Generation Amount for month *j*, Mwh, j=1,…12

P_{RTj}— Actual Market Electricity Price for month *j*, \$/Mwh, j=1,…12

$\overline{P_{RT}}=\frac{1}{12}\sum_{j=1}^{12}P_{RTj}$ — Mean of Actual Annual Market Electricity Price, \$/Mwh

Equation (4-1) is the objective function pursuing to maximize the expected annual revenue of the project. Each month, the IPP gets paid for the actual delivered quantity times the contract price, and at the end of the year, the accumulated delivery $\sum_{j=1}^{12}Q_{RTj}\,, j=1,\ldots 12$ is calculated to be compared with the contract quantity. If the actual delivery is more than what is contracted, $\sum_{j=1}^{12}Q_{RTj}\ge\bar{Q}$, then the IPP will be settled for the additional amount with the outperformance price $\overline{P_O}$, making the revenue as $\bar{P}\cdot\bar{Q}+\overline{P_O}\cdot\left(\sum_{j=1}^{12}Q_{RTj}-\bar{Q}\right)$. On the other hand, if the delivery doesn't hit the contracted amount, $\sum_{j=1}^{12}Q_{RTj}\le\bar{Q}$, then the deficiency will be made up for by the mean price of the market spot price, realized as a negative revenue, making the revenue as $\bar{P}\cdot\bar{Q}-\overline{P_{RT}}\cdot\left(\bar{Q}-\sum_{j=1}^{12}Q_{RTj}\right)$.

Expression (4-2) is a non-regret constraint that represents the buyer's willingness to sign the contract, where the regret is the difference between the cost of electricity bought from the contract minus that is bought directly from the wholesale market. Since we assume a large buyer, who has higher demand than possible delivery from the project, that is $Q_{buyer} \gg \sum_{j=1}^{12} Q_{RTj}$. The cost for the buyer to pay for its electricity bill through the contract can be expressed as:

$$\begin{cases} \bar{P} \cdot \bar{Q} + \overline{P_O} \cdot \left(\sum_{j=1}^{12} Q_{RTj} - \bar{Q} \right) + \overline{P_{RT}} \cdot \left(Q_{buyer} - \sum_{j=1}^{12} Q_{RTj} \right) & if \sum_{j=1}^{12} Q_{RTj} \geq \bar{Q} \\ \bar{P} \cdot \bar{Q} + \overline{P_{RT}} \cdot (Q_{buyer} - \bar{Q}) & if \sum_{j=1}^{12} Q_{RTj} < \bar{Q} \end{cases}$$

Combined, the cost from the contract can be written as:

$$\bar{P} \cdot \bar{Q} + \overline{P_O} \cdot max\left(\left(\sum_{j=1}^{12} Q_{RTj} - \bar{Q}\right), 0\right) + \overline{P_{RT}} \cdot min\left(\left(\sum_{j=1}^{12} Q_{RTj} - \bar{Q}\right), 0\right) + \overline{P_{RT}} \cdot \left(Q_{buyer} - \sum_{j=1}^{12} Q_{RTj}\right)$$

Meanwhile, the total cost for the buyer to purchases the electricity directly from the market is:

$$Cost_{Buyer}(Market) = \overline{P_{RT}} \cdot Q_{buyer}$$

Hence, the non-regret constraint (4-2) can be written as:

$$E\left[\bar{P} \cdot \bar{Q} + \overline{P_O} \cdot max\left(\left(\sum_{j=1}^{12} Q_{RTj} - \bar{Q}\right), 0\right) + \overline{P_{RT}} \cdot min\left(\left(\sum_{j=1}^{12} Q_{RTj} - \bar{Q}\right), 0\right) - \overline{P_{RT}} \cdot \sum_{j=1}^{12} Q_{RTj}\right] \leq 0$$

Moreover, we define another variable $Q_{max} = max\left(\sum_{j=1}^{12} Q_{RTj}, \bar{Q}\right)$, with which another two constraints would be added to the model, and the max and min function in the objective and constraints can be replaced as:

$$max\left(\left(\sum_{j=1}^{12} Q_{RTj} - \bar{Q}\right), 0\right) = Q_{max} - \bar{Q}$$

$$min\left(\left(\sum_{j=1}^{12} Q_{RTj} - \bar{Q}\right), 0\right) = \sum_{j=1}^{12} Q_{RTj} - Q_{max}$$

Since the problem treat the parameter deterministic as estimations from historic data or forecasting, the problem can be finally expressed as (4-4) to (4-8) and solved directly through some nonlinear optimization techniques.

$$max\ \bar{P} \times \bar{Q} + \overline{P_O} \cdot (Q_{max} - \bar{Q}) + E[\overline{P_{RT}}] \cdot \left(E\left[\sum_{j=1}^{12} Q_{RTj}\right] - Q_{max} \right) \tag{4-4}$$

Subject to

$$\bar{P} \cdot \bar{Q} + \overline{P_O} \cdot \left(Q_{max} - \bar{Q}\right) - E[\overline{P_{RT}}] \cdot Q_{max} \leq 0 \tag{4-5}$$

$$\bar{P} \geq \overline{P_O} \tag{4-6}$$

$$Q_{max} \geq E\left[\sum_{j=1}^{12} Q_{RTj}\right] \tag{4-7}$$

$$Q_{max} \geq \bar{Q} \tag{4-8}$$

4.4.2 Improved Strategy for Annual Settlement Contract under Uncertainty: Strategy S2

Strategy S2 is an improved strategy on top of Strategy S1, where the contract terms are based on an annual settlement with monthly payment schedule. The key improvement in this strategy is that it treats the wind resource and electricity price as stochastic parameters. Meanwhile, the constraints associated with the Conditional Value-at-Risk (CVaR) are added to the model as the risk management module. The stochastic programming for Strategy S2 can be formulated as (4-9) to (4-12):

$$max\ E\left[\bar{P} \times \bar{Q} + \overline{P_O} \cdot max\left(\left(\sum_{j=1}^{12} Q_{RTj} - \bar{Q}\right), 0\right) + \overline{P_{RT}} \cdot min\left(\left(\sum_{j=1}^{12} Q_{RTj} - \bar{Q}\right), 0\right)\right] \tag{4-9}$$

Subject to

$$\phi_\beta\left(\bar{Q}, \bar{P}, \overline{P_O}, Q_{RTj}, \overline{P_{RT}}\right) \leq w \tag{4-10}$$

$$pr\left(Cost_{Buyer}(PPA) - Cost_{Buyer}(Market) \leq 0\right) \geq a \tag{4-11}$$

$$\bar{P} \geq \overline{P_O} \tag{4-12}$$

Where

w— Threshold for the CVaR of the settlement cash flow

a— Confidence level for the chance constraint

There are two main modifications made on the Strategy S1 deterministic model. Firstly, in order to address the stochastic feature with the anticipative decision variables, chance constraints (4-11) are used to replace the traditional deterministic regret constraints to explicitly deal with randomness associated with buyer's cost. With the chance constraint, the buyer is only willing to sign the contract when the probability that the regret negatively exceeds a pre-defined confidence level a. The higher the a is, the more risk-averse the buyer is, and usually lower profit the seller can get.

Since the buyer of a PPA also considers the contract as a one-time decision making, the chance constraint should be based on the whole year. Therefore, there is only one chance constraint in terms of the difference of the total cost, as shown in (4-13), where the stochastic variables are the mean market price $\overline{P_{RT}}$ in terms of the monthly market price P_{RTj} and the monthly generation quantity $Q_{RTj}, j = 1, \ldots 12$.

$$\begin{gathered} Pr\left(\bar{P} \cdot \bar{Q} + \overline{P_O} \cdot max\left(\left(\sum_{j=1}^{12} Q_{RTj} - \bar{Q}\right), 0\right) + \overline{P_{RT}} \cdot min\left(\left(\sum_{j=1}^{12} Q_{RTj} - \bar{Q}\right), 0\right) - \right. \\ \left. \overline{P_{RT}} \cdot \sum_{j=1}^{12} Q_{RTj} \leq 0\right) \geq a \end{gathered} \tag{4-13}$$

The second modification for the model is adding the (4-10), a constraint that use the Conditional Value-at-Risk (CVaR) to control the risks of the settlement revenue stream, by defining tolerance level β and loss threshold w. The CVaR risk function $\phi_\beta\left(\bar{Q}, \bar{P}, \overline{P_O}, Q_{RTj}, \overline{P_{RT}}\right)$, by definition, measures the conditional expectation of the annual loss associated with stochastic parameters Q_{RTj} and $\overline{P_{RT}}$, relative to that loss being $\alpha_\beta(\bar{Q}, \bar{P}, \overline{P_O}, Q_{RTj}, \overline{P_{RT}})$ or larger. The CVaR risk function for this problem can be written as

$$\phi_\beta(\bar{Q}, \bar{P}, \overline{P_O}, Q_{RTj}, \overline{P_{RT}}) \tag{4-14}$$

$$= (1-\beta)^{-1} \times \iint_{-Revenue_j \geq \alpha_\beta(\bar{Q}, \bar{P}, \overline{P_O}, Q_{RTj}, \overline{P_{RT}})} f(\bar{Q}, \bar{P}, \overline{P_O}, Q_{RTj}, \overline{P_{RT}}) p(Q_{RTj}, \overline{P_{RT}}) dQ_{RTj} d\overline{P_{RT}}$$

Where $\alpha_\beta(x) = min(\alpha \in \mathbb{R}: \Psi(x, \alpha) \geq \beta)$, is known as the β-VaR for variable *x*. And $f(\bar{Q}, \bar{P}, \overline{P_O}, Q_{RTj}, \overline{P_{RT}})$ is the annual loss function (negative revenue), which can be expressed as:

$$f(\bar{Q}, \bar{P}, \overline{P_O}, Q_{RTj}, \overline{P_{RT}}) = -Revenue \tag{4-15}$$

$$= -\bar{P} \times \bar{Q} - \overline{P_O} \cdot max\left(\left(\sum_{j=1}^{12} Q_{RTj} - \bar{Q}\right), 0\right) - \overline{P_{RT}} \cdot min\left(\left(\sum_{j=1}^{12} Q_{RTj} - \bar{Q}\right), 0\right)$$

Detailed mathematical transformation for the CVaR constraint will be addressed later to discuss the solvability of this stochastic program.

4.4.3 Monthly Settlement Contract: Strategy S3

Instead of annual settlement, we consider a more complicated monthly settlement as the third contract design strategy. The decision variables in this problem are on a monthly base. Altogether there will be 12×3 decision variables for the whole year, which are the monthly contract amount, the monthly contract price, and the monthly outperformance price. It is worth notice that for each month, the decision variables $(\overline{Q_J}, \overline{P_J}, \overline{P_{OJ}}), j = 1 \dots 12$ can be assumed to be independent, thus the large problem can be separated into 12 independent monthly problems, and each has 3 decision variables. For month *j*, the problem can be expressed as:

$$max\, E\left[\overline{P_J} \times \overline{Q_J} + \overline{P_{OJ}} \cdot max\left(\left(Q_{RTj} - \overline{Q_J}\right), 0\right) + P_{RTj} \cdot min\left(\left(Q_{RTj} - \overline{Q_J}\right), 0\right)\right] \tag{4-16}$$

Subject to

$$\phi_{\beta j}\left(\overline{Q_J}, \overline{P_J}, \overline{P_{OJ}}, Q_{RTj}, P_{RTj}\right) \leq w_j$$

$$pr_j\left(Cost_{Buyer}(PPA) - Cost_{Buyer}(Market) \leq 0\right) \geq a$$

$$\overline{P_J} \geq \overline{P_{OJ}}$$

Where the formulas for the CVaR constraints and the chance constraints are both modified for a monthly base.

Applying this method, the revenue will be settled for each month by comparing the actual delivery amount and the contracted amount, as what is done annually with the first two strategies. The reason for proposing this strategy is trying to capture the significant differences of the parameters among different months. With the seasonal trend and the high volatility of the monthly electricity price, an annual contract price cannot represent accurately the value of the generated electricity for each month. As what is discussed in the Strategy S2, the annual price and generation amount are set at a compromised level, where the revenues for each month are averaged out. As the result, the volatilities of the monthly cash flow are not controlled effectively. With this new strategy S3, the contract price and power delivery amount solved are expected to have a seasonal trend that is correlated to the forecasting of the electricity price and the power generation. This strategy grants both parties with more degree of freedom when designing their contract, while of course with the cost of higher problem complexity and more calculation time.

4.4.4 Contract with Annual Settlement and Monthly Price Terms: Strategy S4

Although strategy S3 is expected to be more accurately capture the uncertainty of the stochastic variables, one drawback of the strategy S3 is that the monthly volatility is realized instantly without a buffer. While if with an annual settlement, all the deviations are pushed to be settled at the end of the year, and the positive and negative fluctuates can be cancelled out.

Therefore, as strategy S4, we propose a combination of the strategy S2 and S3, in which the term of price is monthly base, while the contract is to be settled annually. More specifically, in each month, the buyer will be paying for the amount of the actual delivery times the monthly price $\overline{P_J}$, while at the end of the year, the accumulated delivery will be calculated to compare with the annual contract amount $\bar{Q}$ and settle with the annual outperformance price $\overline{P_O}$ or the annual mean of the market price $\overline{P_{RT}}$. With this design, the problem can be expressed as:

$$max\,E\left[\sum_{j=1}^{12}(Q_{RTj} \times \overline{P_j}) + (\overline{P_O} - \frac{1}{12}\sum_{j=1}^{12}\overline{P_j}) \cdot max\left(\left(\sum_{j=1}^{12} Q_{RTj} - \bar{Q}\right), 0\right) + \overline{P_{RT}} \cdot min\left(\left(\sum_{j=1}^{12} Q_{RTj} - \bar{Q}\right), 0\right)\right] \tag{4-17}$$

Subject to

$$\phi_{\beta j}(\bar{Q}, \overline{P_J}, \overline{P_O}, Q_{RTj}, P_{RTj}) \le w_j \tag{4-18}$$

$$pr\big(Cost_{Buyer}(PPA) - Cost_{Buyer}(Market) \le 0\big) \ge a$$

$$\overline{P_J} \ge \overline{P_O}$$

Where the objective still consider the annual revenue, while with different price for each month. Meanwhile, similar to strategy S3, this strategy controls the monthly cash flow volatility with the monthly CVaR constraint. However, since the buyer still evaluates the contract as an annual package, the chance constraint is expressed of buyer's annual cost.

4.5 ***Solvability of the Model***

Figure 4-1 illustrates the cash flow of different strategies. Since each strategy follow different schedule and settlement policy, the patterns and detailed amount of the cash flow vary from each other.

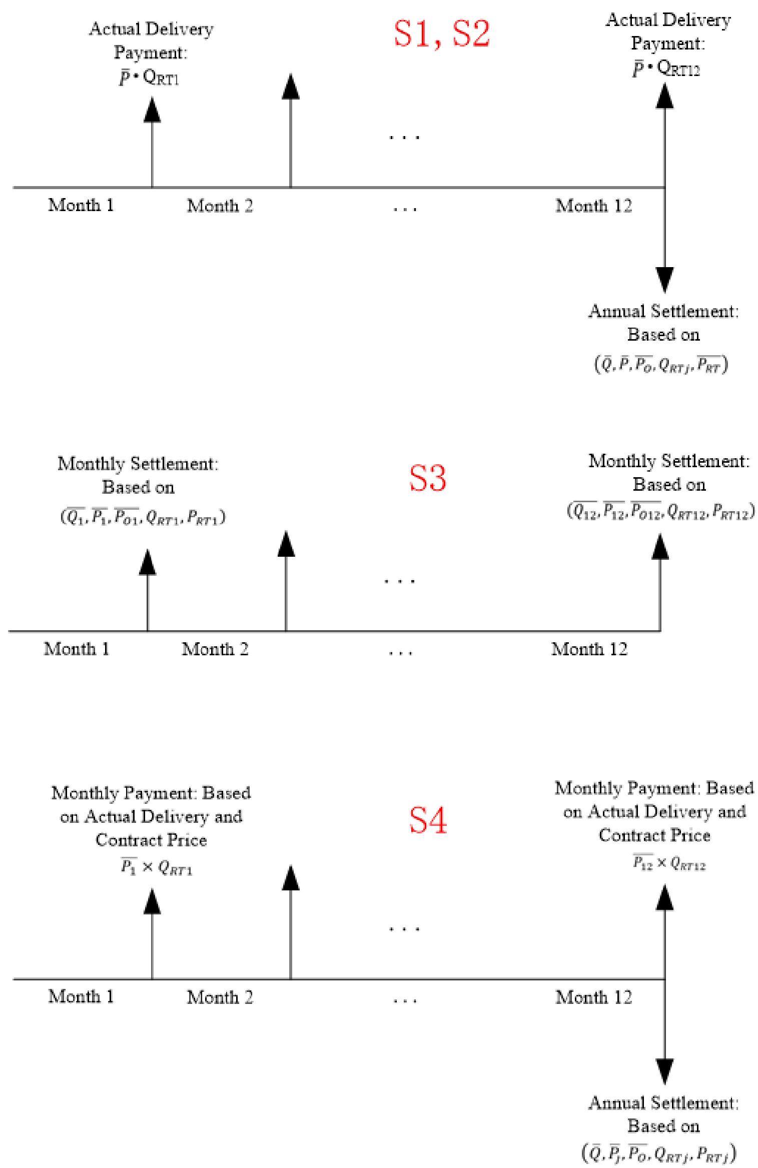


Figure 4-1 Cash Flow for Four Different Strategies

Table *4-1* summarizes the key features of the four different strategies. As discussed, strategy S2 to S4 are formulated as stochastic programming, and each of them embraces different decision variables.

Table 4-1 Summary for Four Different Strategies

Strategy	Settlement	Risk Control	Approach	Variables
S1	Annually	No	Forecasting	Annual Delivery Quantity $\bar{Q}$, Annual Price $\bar{P}$, Annual Outperformance Price $\overline{P_O}$
S2	Annually	Yes	Stochastic	Annual Delivery Quantity $\bar{Q}$, Annual Price $\bar{P}$, Annual Outperformance Price $\overline{P_O}$
S3	Monthly	Yes	Stochastic	Monthly Delivery Quantity $\overline{Q_J}$, Monthly Price $\overline{P_J}$, Monthly Outperformance Price $\overline{P_{OJ}}$
S4	Annually with Monthly Price	Yes	Stochastic	Annual Delivery Quantity $\bar{Q}$, Monthly Price $\overline{P_J}$, Annual Outperformance Price $\overline{P_O}$

Now that we have all models for the four strategies built, the next step is to deal with the solvability of the models. Some of the problems are relatively easy to solve through some classic mathematical processes, such as the deterministic quadratic optimization problem of strategy S1. On the other hand, the other stochastic problems may require some simulation techniques and heuristic algorithms to take care of the sampling and searching procedure. Meanwhile, in order to deal with the troublesome mathematical properties of the CVaR constraint, some specific methodologies will be utilized to transform the problems to solvable formulations. In order to illustrate the process clearly, we take strategy S4 as example. The methodology can be applied to strategy S2 and S3 similarly.

4.5.1 Constraints for Conditional Value-at-Risk (CVaR)

We first consider how to deal with the CVaR constraint. It is proved by (Krokhmal, Palmquist, and Uryasev 2002) that in a general form, if $R(X)$ is concave and $\phi_\beta(X)$ and set X are convex, then the following two problems generate the same efficient frontier.

Problem 1: $min -R(x) \;\; s.t. \phi_\beta(x) \leq \omega, x \in X.$

Problem 2: $min\, \phi_\beta(x) - \mu R(x)\,, x \in X, \mu \geq 0.$

Where μ is the weight allocated between the revenue and risk control, depending on each cases. Usually, risk-averse project owner will choose smaller μ.

Meanwhile, since the problem for strategy S4 constructs *12* constraints of monthly CVaR, $\phi_{\beta j}(x), j = 1, \dots 12$. The CVaR in the objective should be replaced by the mean of monthly CVaR. The problem 2 can be further extended to problem 2':

Problem 2': $min \frac{1}{12} \sum_j \phi_{\beta j}(x) - \mu R(x), x \in X, \mu \geq 0, j = 1, \dots 12.$

Furthermore, in order to deal with the troublesome mathematical properties of the β-CVaR $\phi_\beta(X)$, (Rockafellar and Uryasev 2000) proposed a methodology by defining a simpler expression $F_\beta(x, \alpha)$ with its convexity in the variable α. Hence, instead of determining a vector x that yields the minimization for the combination of β-CVaR and the expected profit, one can equivalently minimize the combination of $F_\beta(x, \alpha)$ and the expected profit. The defined $F_\beta(x, \alpha)$ can be used instead of $\phi_\beta(x)$ to solve the problem 2, which makes the following problem 3 equivalent to the original problem 1.

Problem 3: $min \frac{1}{12} \sum_j F_{\beta j}(x, \alpha) - \mu R(x), x \in X, \mu \geq 0, j = 1, \dots 12.$

Applying this methodology, the *F* functions of the monthly CVaR problems can be defined as follows:

$$F_{\beta j}\left(\overline{Q}, \overline{P_j}, \overline{P_O}, Q_{RTj}, P_{RTj}, \alpha\right) \tag{4-19}$$

$$= (1-\beta)^{-1} \times \iint_{Q_{RTj}, P_{RTj} \in \mathbb{R}} \left\{-Revenue_j - \alpha\right\}^{+} p\left(P_{RTj}, Q_{RTj}\right) dQ_{RTj} dP_{RTj}$$

Where

$$\{t\}^{+} = \begin{cases} t & when\ t > 0, \\ 0 & when\ t \leq 0. \end{cases}$$

And the monthly revenues functions are given by:

When $j = 1, \dots 11,$

$$Revenue_j = Q_{RTj} \times \overline{P_J} \tag{4-20}$$

When j=12,

$$Revenue_j = Q_{RTj} \times \overline{P_J} + \left(\overline{P_O} - \frac{1}{12}\sum_{j=1}^{12}\overline{P_J}\right) \cdot max\left(\left(\sum_{j=1}^{12} Q_{RTj} - \bar{Q}\right), 0\right) + \overline{P_{RT}} \cdot min\left(\left(\sum_{j=1}^{12} Q_{RTj} - \bar{Q}\right), 0\right) \tag{4-21}$$

Then the original problem is equivalent to the following (4-22), where $E\left[Revenue\left(\bar{Q}, \overline{P_J}, \overline{P_O}, Q_{RTj}, P_{RTj}\right)\right]$ and $\widetilde{F_{\beta J}}\left(\bar{Q}, \overline{P_J}, \overline{P_O}, Q_{RTj}, P_{RTj}, \alpha\right)$ are given by (4-17) and (4-19):

$$min \frac{1}{12}\sum_{j} F_{\beta j}\left(\bar{Q}, \overline{P_J}, \overline{P_O}, Q_{RTj}, P_{RTj}, \alpha\right) - \mu E\left[Revenue\left(\bar{Q}, \overline{P_J}, \overline{P_O}, Q_{RTj}, P_{RTj}\right)\right] \tag{4-22}$$

Subject to

$$pr\left(Cost_{Buyer}(PPA) - Cost_{Buyer}(Market) \leq 0\right) \geq a$$

$$\overline{P_J} \geq \overline{P_O}, j = 1 \ldots, 12$$

4.5.2 Chance-Constrained Programming (CCP) and Genetic Algorithm (GA)

The problem for strategy S2 to S4 all include a stochastic objective function and both stochastic and deterministic constraints, which makes the whole models formulated as Chance-Constrained Programming (CCP). Due to the non-linear attribute, the optimization problems cannot be transferred to some simple form of linear program problems. Meanwhile, the complicated distribution of different stochastic parameters makes it hard to provide the deterministic equivalent for the chance constraint. Therefore, we are utilizing Genetic Algorithm (GA) to deal with the optimization process for the stochastic programming for strategy S2 to S4.

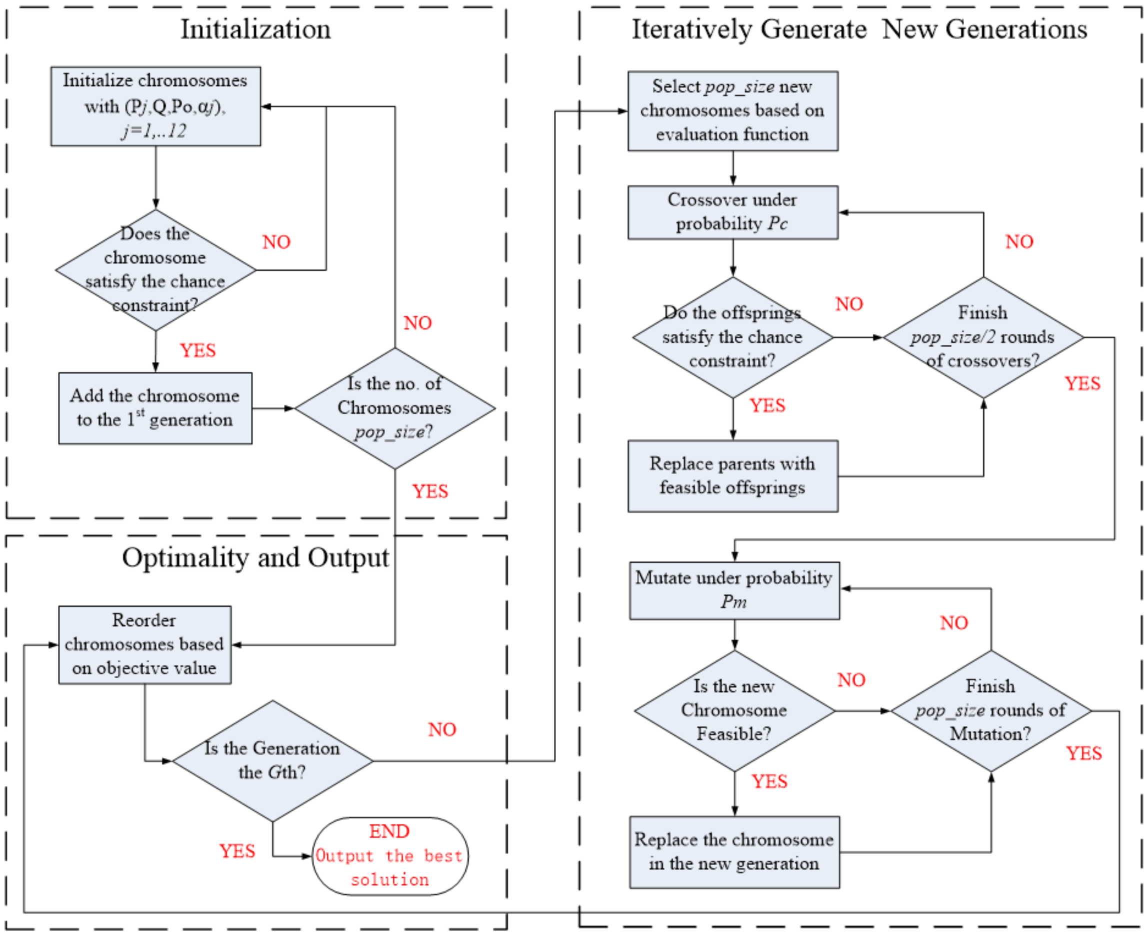


Figure 4-2 Flow Chart for Genetic Algorithm

The framework of performing GA to solve general optimization problems has been summarized in the book of (Liu 2009). Adjusted from that framework, the specific algorithm for our model is proposed as in Figure 4-2.

Specifically, there are 7 steps to finish the procedure.

Step 1: Initialization. Define *pop_size* chromosomes as the number of individuals in a generation. Each chromosome $V_i, i = 1, \dots, pop\_size$ has *N=26* dimensions representing the decision variables $(\bar{Q}, \overline{P_j}, \overline{P_O}, \alpha_j), j = 1, \dots 12$. Iteratively generate *pop_size* feasible chromosomes from constraint check through stochastic simulation. The first generation is initialized.

Step 2: Ranking. Calculate the objective function mean for all chromosomes through stochastic simulation, and rearrange the ranks based on their fitness to the objective. Due to the minimization objective, the smaller the objective mean value, the smaller rank order the corresponding chromosome is allocated.

Step 3: Evaluation. Define the rank-based evaluation function as $Eval(V_i) = c(1-c)^{i-1}, i = 1, \dots, pop\_size$, with which the better the chromosome, the higher evaluation value it will have.

Step 4: Selection. Spin the roulette wheel with the probability proportional to the evaluation value, such that better chromosomes will have more chance to be selected to produce offspring. *pop_size* chromosomes will be selected for further operation.

Step 5: Generation update. Define probability parameters P_c and P_m, with which $P_c \cdot pop\_size$ of the selected chromosomes will be conducted crossover, and $P_m \cdot pop\_size$ of the selected chromosomes will be mutated. A new generation with pop_size updated chromosomes is then established. Each crossover and mutation operation will go through constraint check to make sure the feasibility of the new chromosomes.

Step 6: Repeat step 2 to step 5 to for a given number of cycles *G*, such that *G* generations are generated, and the corresponding objective mean for all $G \cdot pop\_size$ chromosomes are obtained.

Step 7: Report the best chromosome and the minimal objective as the optimal solution.

4.5.3 Simulation

It is worth noted that the GA process for our chance-constrained programming (CCP) is different with that of the classic optimization problems, especially with the module of objective calculation and constraint check. Since the parameters in the objective and chance constraint are stochastic, it is necessary to conduct Monte Carlo simulation to approximate those stochastic functions. (Poojari and Varghese 2008) discussed about the simulation process within the GA framework. Adjust that process with the CVaR in the objective function, we can conduct the simulation as follows (taking Strategy S4 as example).

For stochastic parameter vector $\xi = \left(P_{RTj}, Q_{RTj}\right)$, let $\Omega = (\xi^1, \xi^k, \dots \xi^{|\Omega|})$ denotes the approximate sample space to be generated for each individual chromosome V_i, and H denote the set of chance constraints. In the initialization phase, since there are *pop_size* individuals to be generate in the population, while some would fail the constraint check, hence there are at least $|\Omega| \times pop\_size \times |H|$ function evaluation to be performed. In the evaluation step, all *pop_size* individuals of *G* generations will be calculated for their objective functions, hence there will be $|\Omega| \times pop\_size \times G$ evaluations. In the crossover step, since *pop_size/2* pairs are to be operated crossover, and each population has *G* generations, therefore, it is needed to perform $\frac{1}{2} \times |\Omega| \times pop\_size \times |H| \times G$ crossover evaluation. Similarly in the mutation step, $|\Omega| \times pop\_size \times |H| \times G$ evaluations are to be performed because *pop_size* individuals will be operated mutation.

Specifically, the random vectors P_{RTjk} and $Q_{RTjk}, k = 1, \dots, |\Omega|$ are independently following underlying probability distributions. Accordingly, the stochastic objective and constraints can be computed through the constructed sample space. For each evaluation, the objective function can be obtained through calculating each part with Ω series of vectors Q_{RTjk}, P_{RTjk} $(k = 1, \cdots \Omega)$:

$$\widetilde{F_{\beta j}}\left(\bar{Q}, \overline{P_j}, \overline{P_O}, Q_{RTj}, P_{RTj}, \alpha\right) = \alpha + \frac{1}{\Omega(1-\beta)} \times \sum_{k=1}^{\Omega} \left\{Revenue_{jk} - \alpha\right\}^+ \tag{4-23}$$

Where

$$Revenue_{jk} = Q_{RTjk} \times \overline{P_j} \text{ for } j = 1, \dots 11,$$

$$Revenue_{jk} = Q_{RTjk} \times \overline{P_j} + \left(\overline{P_O} - \frac{1}{12}\sum_{j=1}^{12} \overline{P_j}\right) \cdot max\left(\left(\sum_{j=1}^{12} Q_{RTjk} - \bar{Q}\right), 0\right) + \overline{P_{RTk}} \cdot min\left(\left(\sum_{j=1}^{12} Q_{RTjk} - \bar{Q}\right), 0\right) \text{ for } j = 12$$

And

$$E[Revenue(\cdot)] = \frac{1}{\Omega}\sum_{k=1}^{\Omega}\left[\sum_{j=1}^{12}(Q_{RTjk} \times \overline{P_j}) + (\overline{P_O} - \frac{1}{12}\sum_{j=1}^{12}\overline{P_j}) \cdot max\left(\left(\sum_{j=1}^{12} Q_{RTjk} - \bar{Q}\right), 0\right)\right.$$
$$\left. + \overline{P_{RTk}} \cdot min\left(\left(\sum_{j=1}^{12} Q_{RTjk} - \bar{Q}\right), 0\right)\right]$$

And the value for the chance constraint is the frequency with which the current solution satisfies the constraints. Let n_j be the number of random vectors that satisfy the chance constraints. Then with each constraint check, the chance constraints are evaluated as:

$$pr_j(\cdot) = \frac{n_j}{\Omega}, j = 1, \cdots, 12 \tag{4-24}$$

The (4-24) is also referred to when conducting the Monte Carlo simulation for the initialization.

4.6 Case Study for Cape Wind Project

The Cape Wind project is again referred to as the case study for this chapter. In order to make the strategies comparable with each other, different strategy will be applied with same assumptions associated with the market, the competitor, the buyer and the wind IPP itself. The information collected from the power market and the meteorology station will be processed according to different need of strategy setup. For example, the sampling seed is established based on monthly data, instead of hourly like chapter three.

4.6.1 Results for Different Strategies

With the stochastic information obtained, we are able to run the programs for each of the four strategies. The strategy S1 will be solved though the MATLAB® nonlinear solve system, and strategy S2 to S4 will be solved through the coded GA programming also through MATLAB®. Table 4-2 summaries the parameters for the GA programing for each strategy:

Table 4-2 Parameters for Stochastic GA Programming Setup

	S2	S3 (for each month)	S4
Number of Variable, N	4	4	26
Size of Population, K=10*N	40	40	260
Number of Generation, G=10*K	400	400	2600
Number of Sampling, Omega	1000		
Probability of Crossover, Pc	0.7		
Probability of Mutation, Pm	0.1		

In this part, the solutions of each model will first be discussed with some observations, then some statistics analysis an out-of-sample analysis will be conducted to analyze and compare the performance of different strategies in the next part.

1. Solutions for Strategy S1

For strategy S1, we established the model for a nonlinear programming which can be solved directly from commercially available software. The solution of the program is not unique, where the following two sets of solutions are all optimized and indifferent:

(1) $\bar{P} = \overline{P_{RT}}, \bar{Q} = \overline{Q_{RT}}, \overline{P_O}\ is\ free$

(2) $\bar{P} = \overline{P_O} = \overline{P_{RT}},\ \bar{Q}\ is\ free$

The solutions show that the contract price will be set as equal to the expected market price. Meanwhile, either that the contract price equals the expected generation, or that the outperformance equals the expected market price will make the total expected revenue maximized and equal to $\overline{P_{RT}} \times \overline{Q_{RT}}$. However, this is true only when the forecast for the electricity generation and electricity price are perfectly accurate, or can be regarded as deterministic parameters.

Among the two options, the first one usually sounds more reasonable to both contract counterparts in practice, which is to settle at the expected price and the expected quantity while negotiating on the outperformance price. As a matter of fact, the two PPA contract signed for the

Cape Wind project also follows this practice. As for the outperformance price, they go for half of the contract price, which is also not uncommon.

With the 1000 sets of samples from the generation amount and market price sampling seeds, we are able to obtain the expected price and quantity as solutions for the first option of strategy S1, and outperformance price is set as half of the contract price, as shown in the Table 4-3.

Table 4-3 Program Solutions for Strategy S1

Contract P ($/Mwh)	Contract Q (Mwh)	Contract Po ($/Mwh)
41.6337	1.6164E+06	20.8169

2. Solutions for Strategy S2

Strategy S2, on the other hand, consider the uncertainty of the parameters, and is set up to be solved by the proposed chance-constraint based genetic algorithm. Based on the same 1000 sets of Monte Carlo simulation from the sampling seeds, the solutions for the Strategy S2 are summarized in the Table 4-4:

Table 4-4 Program Solutions for Strategy S2

Contract P ($/Mwh)	Contract Q (Mwh)	Contract Po ($/Mwh)
41.8036	1.6158E+06	15.1884

Figure 4-3 shows the progressing of the solutions through the evolution procedure of the strategy S2 GA programming. With the 400 generations, the decision variables start with a high volatility in the searching area, get stabilized after around the 100^{th} generation, and progressively moving towards the optimized solution after the 250^{th} generation.

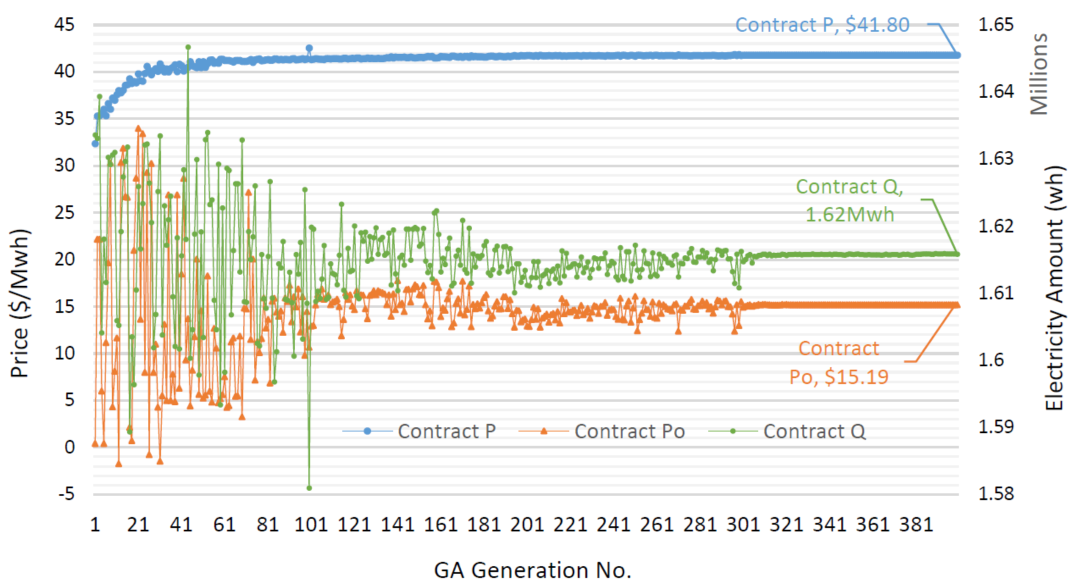


Figure 4-3 Evolution Procedure for GA Programming (Strategy S2)

3. Solutions for Strategy S3

Different with strategy S2, the problem for strategy S3 includes twelve GA programs. Since each problem can be regarded as independent, they are solved separately with the heuristic searching and derive twelve sets of optimized solutions. For all the GA evolution, the algorithms start with large range of searching points, and the chromosomes gradually progress through the iteration goes.

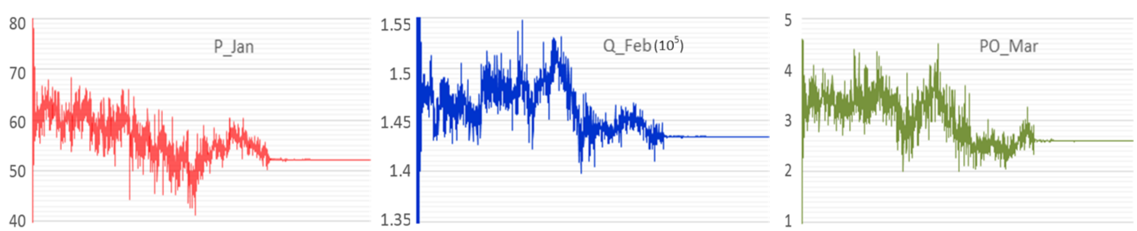


Figure *4-4* shows some of the solutions of the three variables for different months, as examples of detailed evolving procedure.

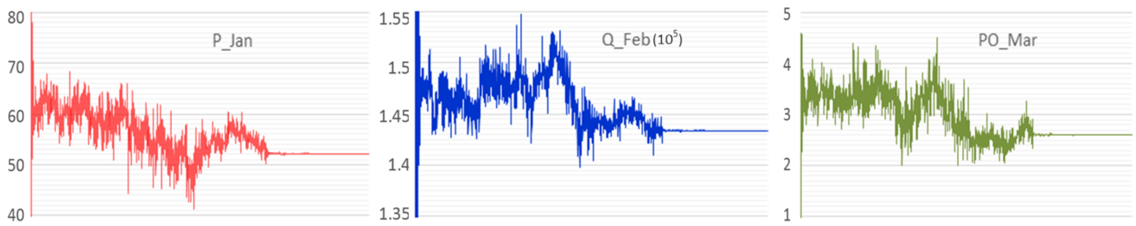


Figure 4-4 Examples of GA Evolving Results for $\bar{P}, \bar{Q}$ and $\overline{P_O}$ (Strategy S3)

Take January as one example of the strategy S3 problems. Among all 400 generations, 228 sets of solutions are unique. The solutions are sorted according to their objective value, which makes the order of the solutions representing the design for contract from bad to good. According to the Figure 4-5, with better contract design, the monthly revenue of the project increases, and the F-function for project risk decreases. The decrease of F-function value causes the corresponding decrease of CVaR, which means that the risk of the project cash flow is better controlled.

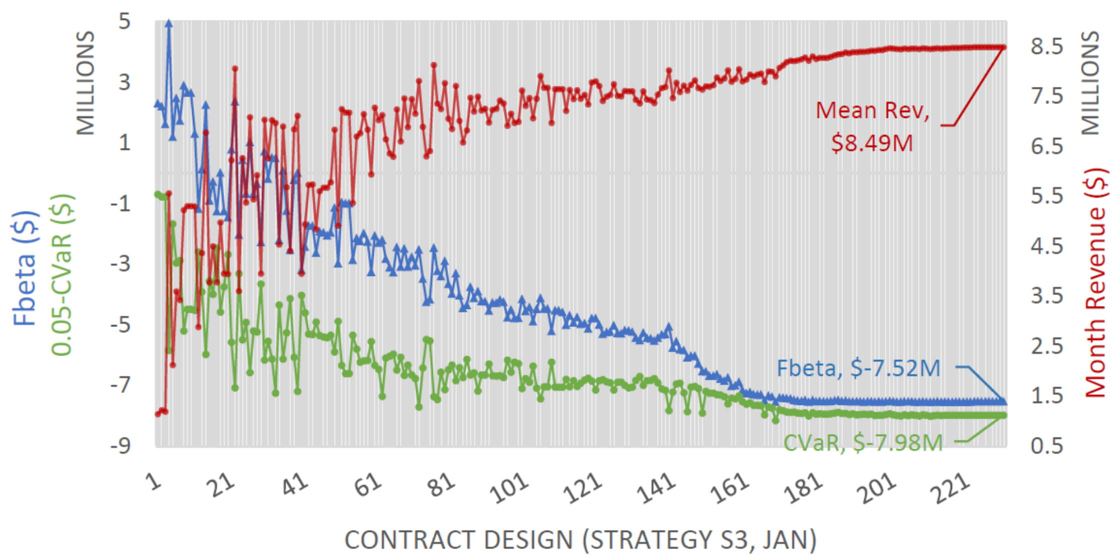


Figure 4-5 GA Result of Monthly Revenue, Fbeta and CVaR (Strategy S3, Jan.)

Meanwhile, with better contract design, the no-regret probability of the buyer is approaching the chance constraint threshold, which is 50% in this case (Figure 4-6). This can be regarded as a benefit sharing mechanism, when approaching the no-regret constraint, the owner is getting higher benefit, while the buyer is pushing to their threshold for accepting the contract. With this being observed, the threshold of the chance constraint is an important negotiation point for the buyer to anticipate the project owner's proposal.

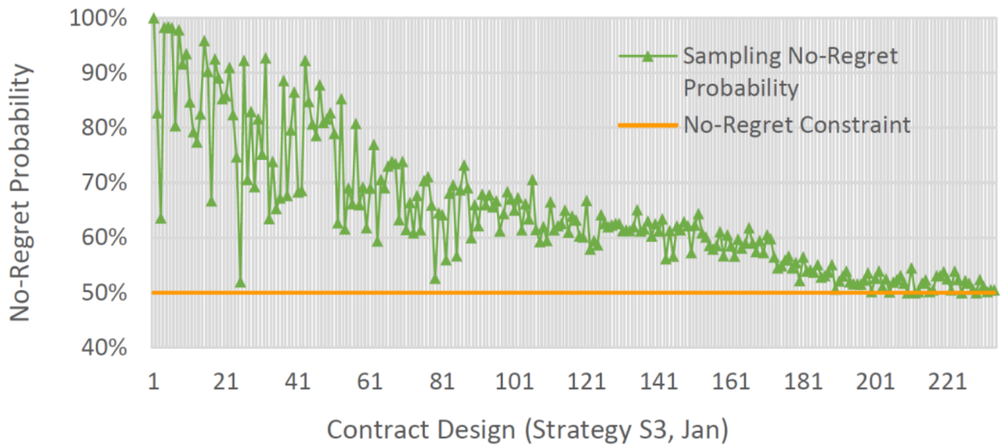


Figure 4-6 GA Result for No-regret Probability

Table 4-5 lists the ultimate solutions for strategy S3's decision variables of each month. And the seasonal trend of the solutions are obviously shown in Figure 4-7. Both the contract quantity and contract price are strictly following seasonal pattern that correlate with the trend of the wind resource and the expected electricity market price. Due to the high instability of the wind resource and market price, the solutions have high volatility, with the range of [\$37.54, \$52.49] and [8.26×10^4Mwh, 1.69×10^5Mwh] respectively. While the outperformance prices don't follow a significant seasonal pattern, nor have obvious relationship with the contract price or the contract generation amount. They are in the small range of [\$7.21, \$12.15].

Table 4-5 Solutions for Strategy S3

	Jan	Feb	Mar	Apr	May	Jun
P	52.49	42.92	38.61	37.76	41.23	41.29
Q	1.62E+05	1.48E+05	1.50E+05	1.32E+05	1.13E+05	8.26E+04
Po	7.21	7.82	12.15	12.13	10.20	8.68
	Jul	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
P	45.60	41.93	38.24	37.54	37.55	50.41
Q	8.54E+04	9.58E+04	1.24E+05	1.56E+05	1.53E+05	1.69E+05
Po	8.77	8.36	11.77	10.32	8.42	10.49

Figure 4-7 Monthly Price *P*, Quantity *Q*, and Outperformance Prices *Po* (Strategy S3)

4. Solutions for Strategy S4

Similar methodology and solution algorithms are applied to the strategy S4, except the decision is based on annual settlement with different monthly contract price. Therefore the decision variables becomes $(\overline{P_j}, \overline{Q}, \overline{P_O}), j = 1, \dots 12$. With the generation number increased to 2600, the GA algorithm succeeds getting the optimized solution, as shown in the Table 4-6. Unlike strategy S3, the solution monthly price $\overline{P_j}$ are not obviously follow the seasonal trend of the expected market price. Instead, they fluctuate around the expected prices. With five months higher than the expected mean, and seven months lower, as shown in Figure 4-8.

Table 4-6 Solutions for Strategy S4

P						***Q***	***Po***
Jan	Feb	Mar	Apr	May	Jun	1.6325E+06	10.542
46.011	48.937	34.352	38.997	37.601	42.563		
Jul	Aug	Sep	Oct	Nov	Dec		
35.367	38.249	34.447	38.127	36.544	58.242		

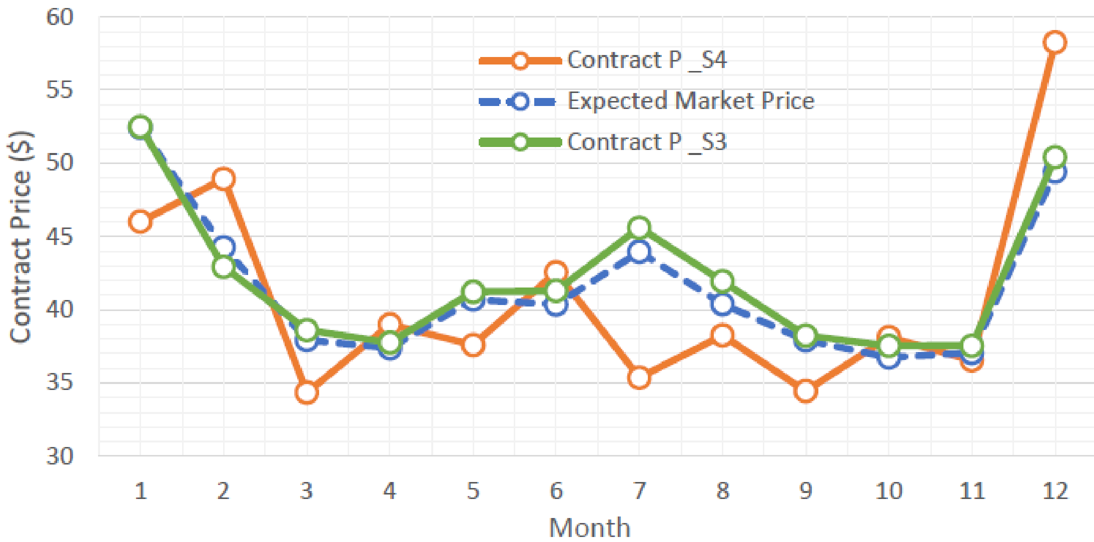


Figure 4-8 Compare of Contract Price *P* with Expected Market Price (Strategy S3, S4)

4.6.2 Performance Comparison of Different Strategies

With all four strategies solved, we now compare the performance of each strategy based on the 1000 samples of the uncertain parameters, and an out-of-sample analysis. The performances are discussed in terms of the revenue pattern, cash flow risks, as well as buyer's attitude for each strategy.

1. Expected Revenue and Risk Control

We start with the expected revenue pattern for different strategies, which are derived through combing the results from each strategy and the 1000 sampling sets.

Observation 4-1. Strategy S2 improves the Strategy S1 in terms of both the expected annual revenue, and the expected cash flow risk.

For strategy S1 and S2, the key difference is that strategy S2 considers the problem as in a stochastic environment, which can merit the project owner to balance or hedge between different scenarios of the uncertain parameters. Therefore, we first compare the two strategies using the metric called the value of Stochastic Solutions (VSS), which assesses the value of knowing and using distributions on future outcomes (Birge and Louveaux 2011). The results of the two strategies, the expected revenue, and the risk measure metrics β-VaR and β-CVaR are summarized in Table 4-7.

Table 4-7 Revenue and Statistics of Solutions for Strategy S1 and S2

	Contract P ($/Mwh)	Contract Q (Mwh)	Contract Po ($/Mwh)	Exp. Annual Revenue ($)	β-VaR of Annual Rev.($)	β-CVaR of Annual Rev. ($)
S1	41.6337	1.6158E+06	20.3843	6.7186E+07	-5.4715E+07	-5.4392E+07
S2	41.8036	1.6142E+06	15.1884	6.7358E+07	-5.5379E+07	-5.5058E+07

As shown in the table, the increase of the expected annual revenue with the stochastic programming, which is also known as the Value of Stochastic Solutions *VSS* is $\$1.72\times10^5$. If we incorporate the CVaR into the evaluation of the stochastic program, we can define a modified $\beta-$VSS, which is the difference of (Rev−CVaR) between the deterministic programming and the stochastic programming. Therefore, in this case

$$\beta-\text{VSS}=(\text{Rev}-\text{CVaR})_{S2}-(\text{Rev}-\text{CVaR})_{S1}=\$8.37\times10^5$$

Observation 4-2. CVaR risk control causes the revenue distribution to have negative skewness.

The expected distributions of the annual revenues for the four strategies are derived as in the Figure 4-9. As shown of the distributions, the revenue from strategy S1 is about symmetric, while the other three strategies are all having negative skewness, which means fatter tail to the right and longer tail to the left. This is mainly because the risk control module in the strategy S2 to S4 are minimizing the one-side CVaR, which tend to push the small revenues towards right. The strategy S1, on the other hand, does not have the risk control mechanism, hence only maximizing the revenue at all levels.

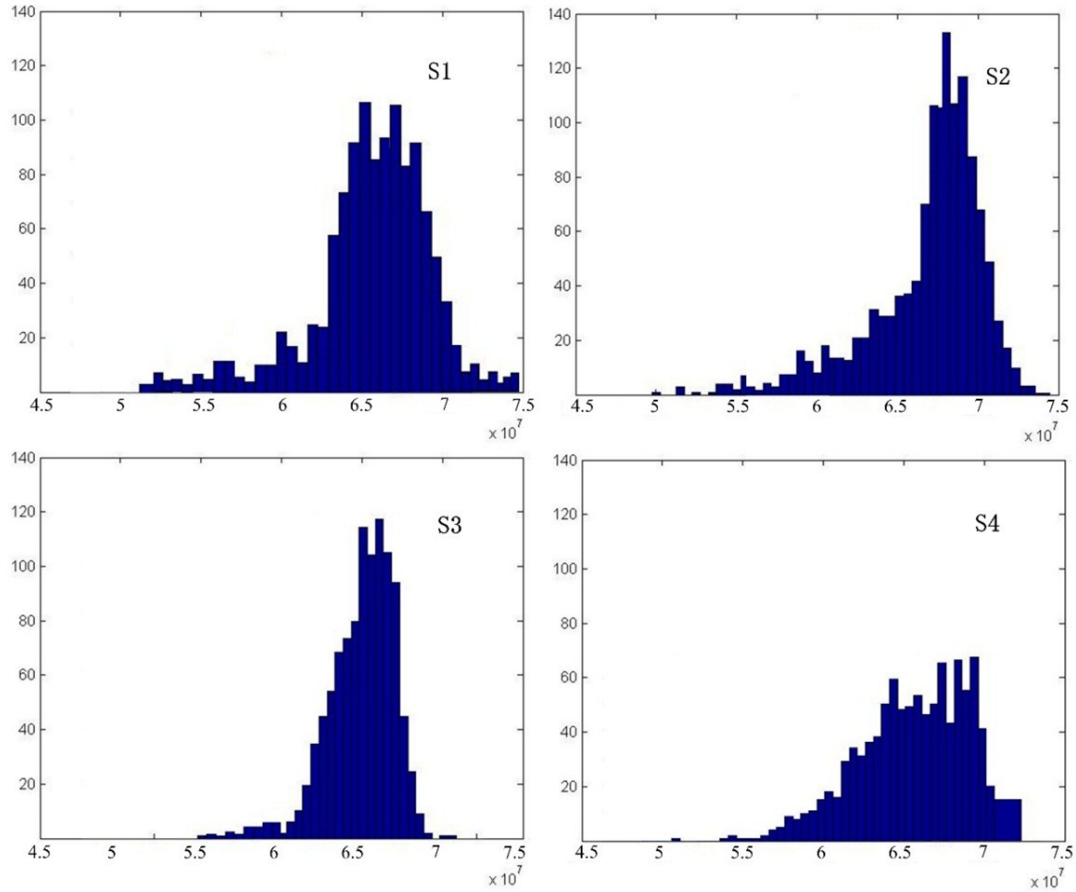


Figure 4-9 Distribution of Annual Revenue for Four Strategies (1000 samples)

Observation 4-3. Strategy S3 and S4 sacrifice the annual revenue and enhance the risk control mechanism, especially largely reduce the monthly cash flow CVaR (Figure 4-10).

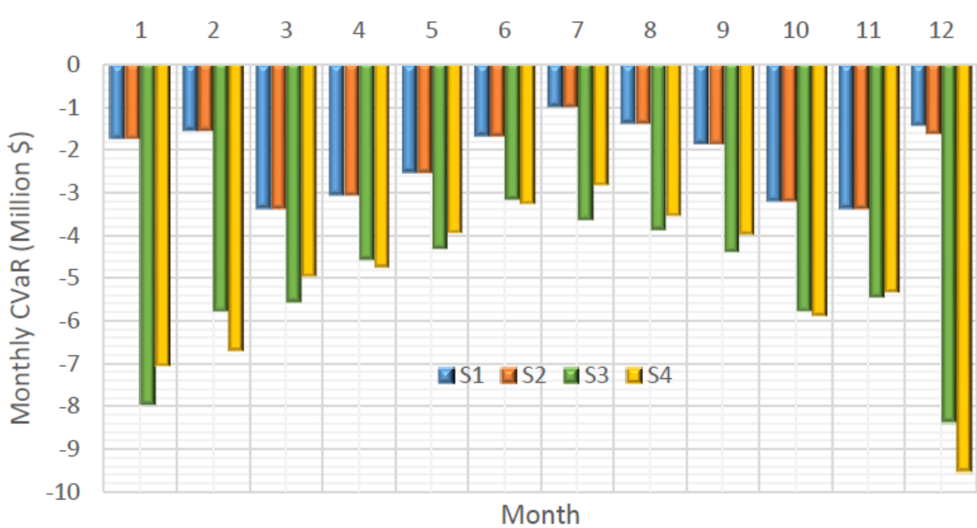


Figure 4-10 Monthly CVaR for Different Strategies

Take strategy S1 as the baseline, the improvement of the expected performance can be converted to a percentage with the metric of revenue and CVaR. As shown in Table 4-8, the strategy S2 to S4 all improve the annual cash flow CVaR by solving the stochastic programming with the risk control module added. Strategy S3 and S4 sacrifice a small portion of the monthly revenue, while significantly increase the risk control of the monthly cash flow. The CVaR amount from strategy S3 and S4 beat both S1 and S2 by more than 100%.

Table 4-8 Improvement from Baseline Strategy S1

	S1	S2	S3	S4
Annual Revenue ($)	6.72E+07	6.74E+07	6.66E+07	6.69E+07
Improve of Annual Revenue (%)		0.26%	-0.87%	-0.40%
Annual CVaR ($)	-5.44E+07	-5.51E+07	-5.57E+07	-5.53E+07
Improve of Annual CVaR (%)		1.22%	2.47%	1.74%
Average Monthly CVaR ($)	-2.20E+06	-2.21E+06	-5.27E+06	-5.17E+06
Improve of Monthly CVaR (%)		0.71%	139.72%	135.18%

The reason behind the performance difference is that the first two strategies are making decisions based on an annual base, and rely on the possibilities that the cash flow fluctuates of different months will cancel out with each other. This is the brighter side that the risks are taken advantage of if the equity holder or debt holder only consider the annual cash flow. However, if the volatility is not specifically controlled, it will become a problem especially when the project is evaluated based on its monthly revenue, or debts be paid back at a monthly base. In those cases, the project owner would want to take monthly settlement strategies S3 or S4.

2. Buyer’s Perspective

Observation 4-4. Although for the four strategies, the buyer’s willingness is guaranteed though the non-regret constraint, the patterns of the buyer’s regret probabilities vary from each other.

Figure 4-11 plots the non-regret probability of the buyer of the 12 months for each strategy. Since the strategy S1, S2 and S4 are based on an annual non-regret constraints, the volatility of the monthly probability is significant. Meanwhile, although the annual constraint is satisfied with the

50% threshold, the monthly non-regret probability could still be less than 50%. The means of the monthly non-regret probability for each strategy are also plotted in the Figure 4-11, with which strategy S4 have the highest probability, and strategy S2 derived the smallest probability. Strategy S3, on the other hand, has a very stable non-regret probability pattern. Since this strategy is made based on monthly settlement, all the monthly non-regret probabilities are forced to be at least 50%. However, the average probability of strategy S3 is not as high as strategy S4 since the decision making for strategy S3 is trying to push the monthly probability towards 50% so as to share more benefit to the project owner.

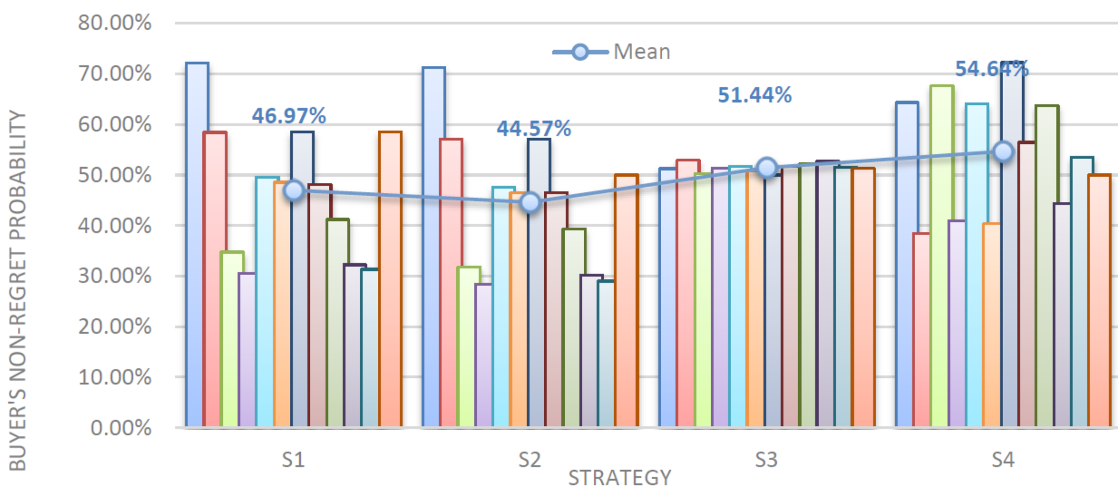


Figure 4-11 Buyer's Non-regret Probability for Four Strategies

3. Out-of-Sample Analysis — Actual Performance for 2013

Out-of-sample is a procedure to analyze the strategy based on the actual data. As applied to our problem, the different strategies that we solved are based on the historic data from 2009 to 2012, now we are using the actual 2013 data to verify the expected result, and analyze the actual performance of the strategies we derived.

Observation 4-5. The out-of-sample result is consistent with the expected performance, which justify the methodology and model building.

The actual value for the uncertain parameters Q and P are derived through the electricity market and the meteorology center database. As shown in the Figure 4-12, the estimation for the generation quantity has a better fit for the estimation for the electricity market price. Even though, the actual win IPP's revenue and buyer's savings follow the expected pattern as discussed previously (Figure 4-13).

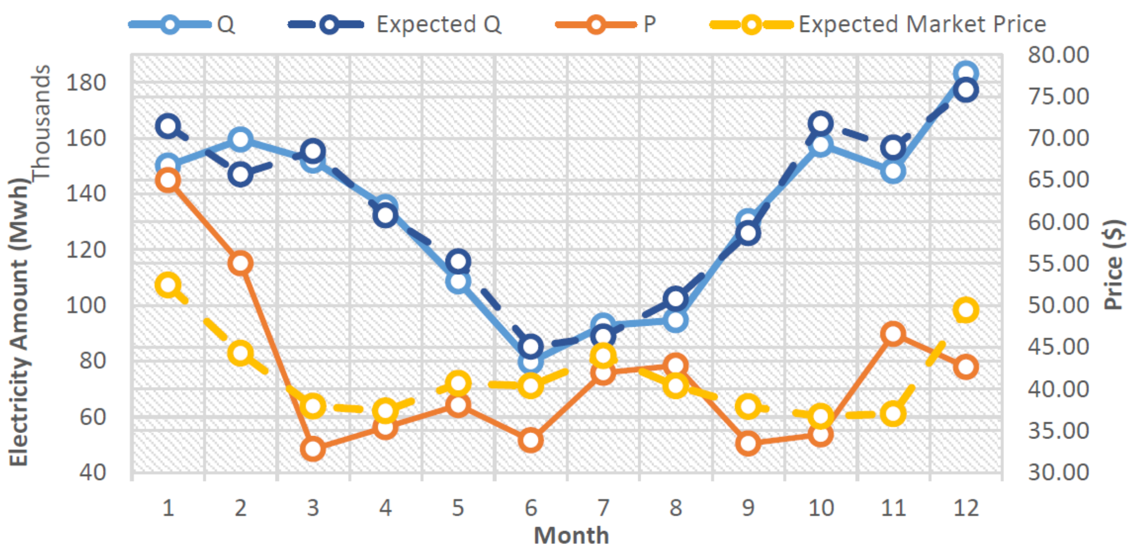


Figure 4-12 Actual VS Expected Value of Uncertain Parameters

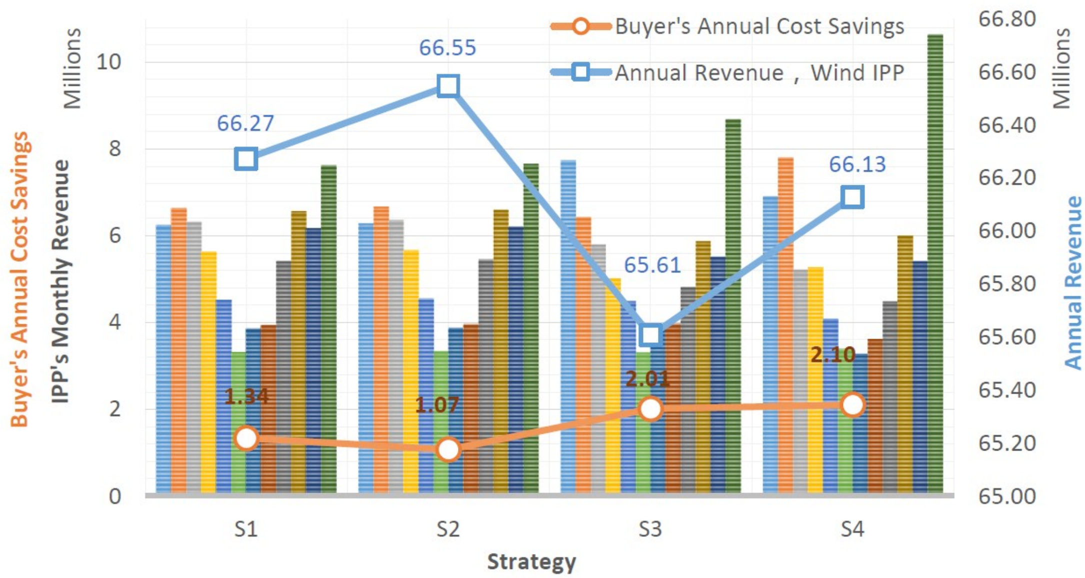


Figure 4-13 Actual Monthly Benefit of Wind IPP and Buyer for 2013

Observation 4-6. The relationship between the project owner and the energy buyer is not a zero-sum game, instead, the revenue and risk control benefit can be shared through the contract terms thus realize a mutual surplus enhancement.

As shown in Figure 4-13. The strategy S2 derives the best annual revenue for the project owner while the least savings for the buyer, and the strategy S3 and S4 get the better benefit for the buyer while sacrifice some of the project owner's revenues. Meanwhile, assume 30% debt at 8% interest rate, 50% tax equity at 8.5% cost and 20% common equity at 12% cost, the average subsidized cost for the wind project is approximate \$40/Mwh (LAZARD 2011), then the annual cost for the cape wind project for year 2013 is $\$6.37\times10^{7}$. Combining the revenue and the cost, we can get both parties' profit through the project, as Table 4-9. Overall, strategy S4 obtains the highest overall surplus.

Table 4-9 Surplus Sharing for the Seller and the Buyer

	S1	**S2**	**S3**	**S4**
Seller's Surplus (\$)	2.60E+06	2.87E+06	1.93E+06	2.45E+06
Buyer's Surplus (\$)	1.34E+06	1.07E+06	2.01E+06	2.10E+06
Overall Surplus (\$)	3.93E+06	3.94E+06	3.94E+06	4.56E+06

4. Overall Evaluation for Different Strategies

Observation 4-7. Among the four different contract design strategies, there is no one that exclusively outperforms. Instead, each of them has its advantage which depends on the need from the project owner and the buyer.

Strategy S1 is the most straightforward strategy that is easy to execute. It obtains reasonable revenue cash flow, and depends the least on the information of the parameter estimation. Strategy S2 incorporate the stochastic nature of the parameters in the model, it is expected to improve the performance based on the additional information of the uncertainties. As a matter of fact, strategy S2 is expected to get the highest annual revenue among all the options, and improves the annual revenue volatility on strategy S1. Strategy S3 addresses the monthly settlement plan, with which it largely enhance the risk control of the monthly cash flow on strategy S1 and S2, and stabilize the buyer's non-regret probability above 50%. As a compromise, the strategy S3 sacrifices a small portion of the revenue. Strategy S4, at last, is a balance between the revenue and the risk control. It obtains higher expected revenue than strategy S3 and improve the annual CVaR of strategy S2. Both strategy S3 and S4 outperform at monthly revenue risk control by a large margin. Meanwhile, the strategy S4 provide the buyer the highest non-regret probability.

In order to systematically evaluate the strategies, we define a five-fold score system, and calculate the normalized scores for all the five criteria. Among all the criteria, weights should be allocated between the easiness to execute the strategy and the strategy effectiveness. We take 0.3 and 0.7 as an example. Specifically, the measure criteria and the calculation references are summarized in the Table 4-10:

Table 4-10 Strategy Evaluation Criteria and Score

		S1	**S2**	**S3**	**S4**	**Calculation References**
Easy to Execute (weight 0.3)		30.000	26.667	23.333	20.000	Relying on Data, Computing Difficulty
Strategy Effectiveness (weight 0.7)	Annual Revenue	25.064	25.128	24.845	24.964	Normalized Annual Revenue (Actual)
	Annual Risk Control	24.716	24.971	25.232	25.080	Normalized Negative Annual CVaR (Expected)
	Monthly Risk Control	14.801	14.907	35.482	34.810	Normalized Reverse Monthly CVaR (Expected)
	Buyer's Satisfaction	19.940	18.899	29.911	31.250	Normalized Buyer's Non-regret Probability (Expected)
Total Score		**68.17**	**66.73**	**87.83**	**87.27**	

According to the result, the strategy S3 ranks the first, strategy S4 second, strategy S1 the third, and strategy S2 the last. Since strategy S3 and S4 does not have substantial difference between each other, they can be regarded as alternatives, and recommended as the improvement for traditional strategy S1. Although strategy S2 enhances a small margin of the S1 in terms of the revenue and risk control, it is not recommended as a replacement mainly due to the additional computational burden and buyer's benefit loss (Figure 4-14).

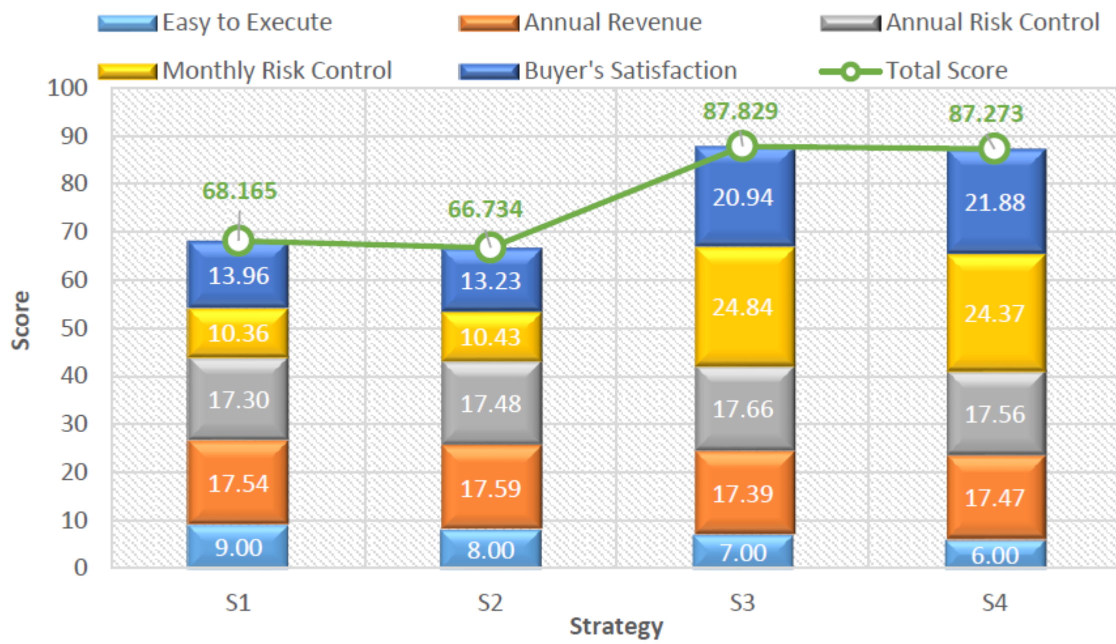


Figure 4-14 Strategy Evaluation Result

4.7 <u>Conclusions</u>

In this section, we consider the long-term offtake strategy through bilateral PPA contract for wind projects. Four different strategies are proposed for different emphasis with regard to settlement schedule, performance-based contract terms, and buyer's non-regret attitude. Applying the strategies to the Cape Wind case study, the analytical solutions for all different strategies are obtained through Genetic Algorithm and stochastic programming. The performances of the strategies are then evaluated through the solutions and the out-of-sample analysis. The strategy S3 and S4 which are more focused on monthly cash flow risk control are recommended as the replacement for traditional deterministic contract design. Some other observations are duly summarized.

Chapter 5. Hybrid Offtake Strategy Design for Wind Project

*5.1 **Introduction***

According to the previous two chapters, wind IPP should either choose a short-term offtake to the spot market, or sign long-term PPA with purchasers, but there is no flexibility to opt between the two. Although some large wind projects are divided into small sub-projects, and are allocated to different offtake strategies, the wind IPP still have no control over the offtake approach for each sub-project. In an uncertain circumstance, however, it is important to hold options during the operation so as to balance or hedge against different scenarios for the volatile exogenous factors (Birge and Louveaux 2011).

As we discussed in chapter three and chapter four, the short-term and long-term strategies have their own pros and cons. The short-term strategy is very sensitive to the stochastic parameters, thus is able to take advantage of the fluctuation at a very short hourly base and is able to capture the revenues that are expectedly maximized. However, the stochastic nature of the electricity market and the wind resource result in a high volatility of the cash flow, thus bring extra uncertainties of the project feasibility and profitability. The risks from the unstable cash flow are the main concerns which prevent many wind IPPs from choosing the short-term strategy. The long-term strategy, on the contrary, is mainly designed for controlling the long-term cash flow risks. The volatility is reduced due to the contract terms such as the price and the quantity that are set as fixed for a month or even a year. As a result, the long-term strategy is effective in stabilizing the cash flow while sacrificing the revenue. Although each strategy is optimized in the previous two chapters, the possibility to combine the two strategies is not yet considered. If both strategies can be effectively integrated, the disadvantages are expected to be offset by the advantages, which will result in a better balance between the revenue and risks.

In this Chapter, an extended hybrid model will be presented, which enables wind IPPs to establish a more flexible mechanism for the electricity production offtake combining the short-term and long-term strategies. A two level stochastic model will be built, with the first level to design the PPA contract with detailed terms before the project starts, and the second level to optimize the allocation of the energy production between the PPA and the spot market. This recourse process will enable the project developer to take into consideration the uncertainties of the weather and the power market during the operation, and plan contract design and negotiation accordingly.

5.2 Two-Level Decision Making for the Hybrid Offtake Strategy

The designing for the hybrid offtake can be regarded as a two-level problem, where the first level is to design the long-term PPA contract, and the second level is to figure out the best short-term offtake strategy at each time point given the contract. The idea is that with the contract signed for the multiple years, the project developer has the flexibility to allocate his generation both to the long-term PPA, and to the spot market, at the real time hourly decision making. This gives the developer the right to adjust his real-time strategy based on the updated estimation for the stochastic variables, while the PPA take the flexibility into consideration, and will guarantee the right for both parties.

The two-level problem is a special case for multilevel programming (MLP), which describes a decentralized decision system where there are a leader and followers. Both the leader and followers have their own decision variables and objective functions, and the leader can only influence the reactions of followers through his own decision variables, while the followers have full authority to decide how to optimize their own objective functions in view of the decisions of the leader and other followers (Liu 2009).

As an analogy to the MLP, our two level decision-making problem describe the developer's hybrid strategy making process where the PPA contract is designed in the first level as a *here-*

and-now decision before knowing the stochastic parameters, and the short-term bidding strategy in the spot market of the second level is to be designed as an approximate *wait-and-see* decision, with more information available (Birge and Louveaux 2011, Carrión, Conejo, and Arroyo 2007). The contract design of the first level is regarded as a one-time decision making, while the operation strategies for the short-term market bidding are time-varying dynamic decision making. The two-level model can be a good fit to treat the different procedures.

As analyzed in the chapter four, the strategy S3 of the PPA contract design with monthly design has the overall best performance, hence we assume the wind IPP will go for the monthly PPA settlement in this hybrid strategy. Furthermore, we assume that within one month, the daily pattern of the wind speed and the electricity market are following the same distribution. With this assumption, the monthly problem can further be approximately decomposed to 30 same daily strategy. Finally, the monthly hybrid problem will be treated as duplicated daily strategies, which are composed of a daily settlement PPA contract offtake plus 24 hourly bidding strategy for spot market offtake.

The two-phase problem can be written as the following general form (5-1). The first phase is the grand problem, which is to decide the terms of the PPA contract so as to maximize the total daily revenue, given the CVaR constrain as risk control and non-regret chance constraint as the buyer's attitude. The decision variable for the first phase are the daily PPA term variables $(\bar{P}, \bar{Q}, \overline{P_O})$, while the short-term strategy $u(t), t = 1, \dots 24$ for the hourly bidding are provided as parameters solved through the second phase. In the second phase, the developer is given the contract with parameters of $(\bar{P}, \bar{Q}, \overline{P_O})$, hence the problem is to make the best hourly bidding decision about the allocation of the generation amount delivering between the spot market and the PPA contract. After obtaining the solution for the daily solution, the monthly contract terms can be directly calculated as $(\bar{P}, 30 \times \bar{Q}, \overline{P_O})$, and the bidding strategies for the 24 hours are duplicated for 30 days as the monthly short-term strategy.

Specifically for one day, the hybrid offtake strategy can be written as:

$$\begin{cases} \max\limits_{\bar{P},\bar{Q},\overline{P_O}} Revenue\left(\bar{P},\bar{Q},\overline{P_O},u^*(t),x^*(t)\ \right), t = 1,\dots T \\ subject\ to \\ \qquad \phi_\beta(\bar{P},\bar{Q},\overline{P_O},u^*(t),x^*(t)) \leq w \\ \quad pr\left(Cost_{Buyer}(PPA) - Cost_{Buyer}(Market) \leq 0\right) \geq a \\ \quad (u^*(t),x^*(t)) solves\ problems \\ \quad \begin{cases} max\ Revenue\left(\bar{P},\bar{Q},\overline{P_O},\ u(t),x(t)\right), t = 1,\dots T \\ subject\ to \\ Time\ Varying\ Constraints \end{cases} \end{cases} \tag{5-1}$$

Where

$\bar{P}$ —Daily electricity price, equals to the Monthly contract price signed in PPA

$\bar{Q}$ —Daily delivery amount, equals to the 1/30 monthly delivery amount signed in PPA

$\overline{P_O}$ —Daily outperformance price, equals to the Monthly outperformance price signed in PPA

$u(t)$ —Hourly electricity amount bidding in the spot market

$x(t)$ —Daily quota realization at time *t*

T—Total number of hours in the effective period of the contract

For the second level problem, an affine controller will be used to solve the time varying dynamic procedure, which assumes that the decision variable is affine to the system output. Applied this problem, the bidding amount for each hour is assumed to be affine to the electricity that has been delivered to the PPA buyer. Given the assumption, the second level problem can obtain a unique analytical solution, which is the bidding strategies for each hour every day, with a specific contract. Detailed mathematical procedure for the affined controller will be discussed separately in the following section.

With the second level solved, the first level problem is essentially trying to find a good design for the contract terms, so that the overall revenue could be maximized. Meanwhile, similar to the previous two chapters, a chance-constraint is used to depict the PPA buyer's non-regret attitude. Therefore, a chance-constraint based Genetic Algorithm (GA) will be used to deal with the iterative search. The GA has been applied in many optimal control problems, and is able to obtain the global optimal solution fairly especially when the optimization problem has multimodal objective functions or irregular search spaces (Holland 1975, Glodberg 1989, Liu 2009). The framework for the GA process is similar to the one summarized in chapter 4.

5.3 Second Level Short-term Bidding Strategy using Affine Controller

5.3.1 Second-level Optimization Problem

We first consider the second level problem, which is an hourly dynamic problem. The central idea is to decide the bidding amount in the spot market for each hour, and the remaining of the generation will be selling to the long-term buyer, which is fed into the monthly quota of the PPA contract. Although the hourly revenues from the spot market are independent, which is only based on the actual generation amount for each hour, the strategy associated with the PPA are time varying as a dynamic process. There is a monthly quantity pre-determined in the contract, which can be regarded as a fix quota for the project developer. At the end of each month, the revenue is settled based on the accumulated delivery amount from each hour comparing with the quota. Therefore, the bidding strategies for each hour not only have the impact on the hourly revenue from the spot market, but also on the final monthly revenue from the PPA contract.

Meanwhile, with the assumption that in one month, the stochastic parameters for each day are following the same pattern, the monthly strategy can be transferred to a daily 24-hour decision making. Figure 5-1 illustrates the process of a daily decision making.

At each hour, the developer should decide on the bidding amount $u(t)$ in the DA market, when the actual generation is realized, the wind IPP will be settled at the RT market, with regard to the day-ahead LMP $P_{DA}(t)$, real-time LMP $P_{RT}(t)$, and day-ahead bidding amount $u(t)$. Different with the settling scheme discussed in chapter 3, we make the following assumptions as the market rules to ensure a fair and manageable market with this hybrid strategy existing:

(1) Due to the reliability concern, the wind producer can only bid at the day-ahead market with the amount less than the expected generation amount.

(2) For the sake of reliability, with a hybrid strategy-taking IPP, if the actual generation is more than the day-ahead bidding amount, the actual delivery should be equal to the bidding amount. Instead, the remaining electricity should be delivered to the bilateral contract buyer.

(3) If the actual generation is less than what the IPP bids in the day-ahead market, the difference will be settled as a negative balance with the real-time market price.

With the assumptions, the hourly revenue can be written as:

$$Hourly\ Revenue_{Spot\ Market} = P_{DA}(t) \cdot u(t) + P_{RT}(t) \cdot min\left(\left(Q(t) - u(t)\right), 0\right) \tag{5-2}$$

Therefore, the daily revenue from the spot market is:

$$Daily\ Revenue_{Spot\ Market} = \sum_{t=1}^{24} P_{DA}(t) \cdot u(t) + P_{RT}(t) \cdot min\left(\left(Q(t) - u(t)\right), 0\right) \tag{5-3}$$

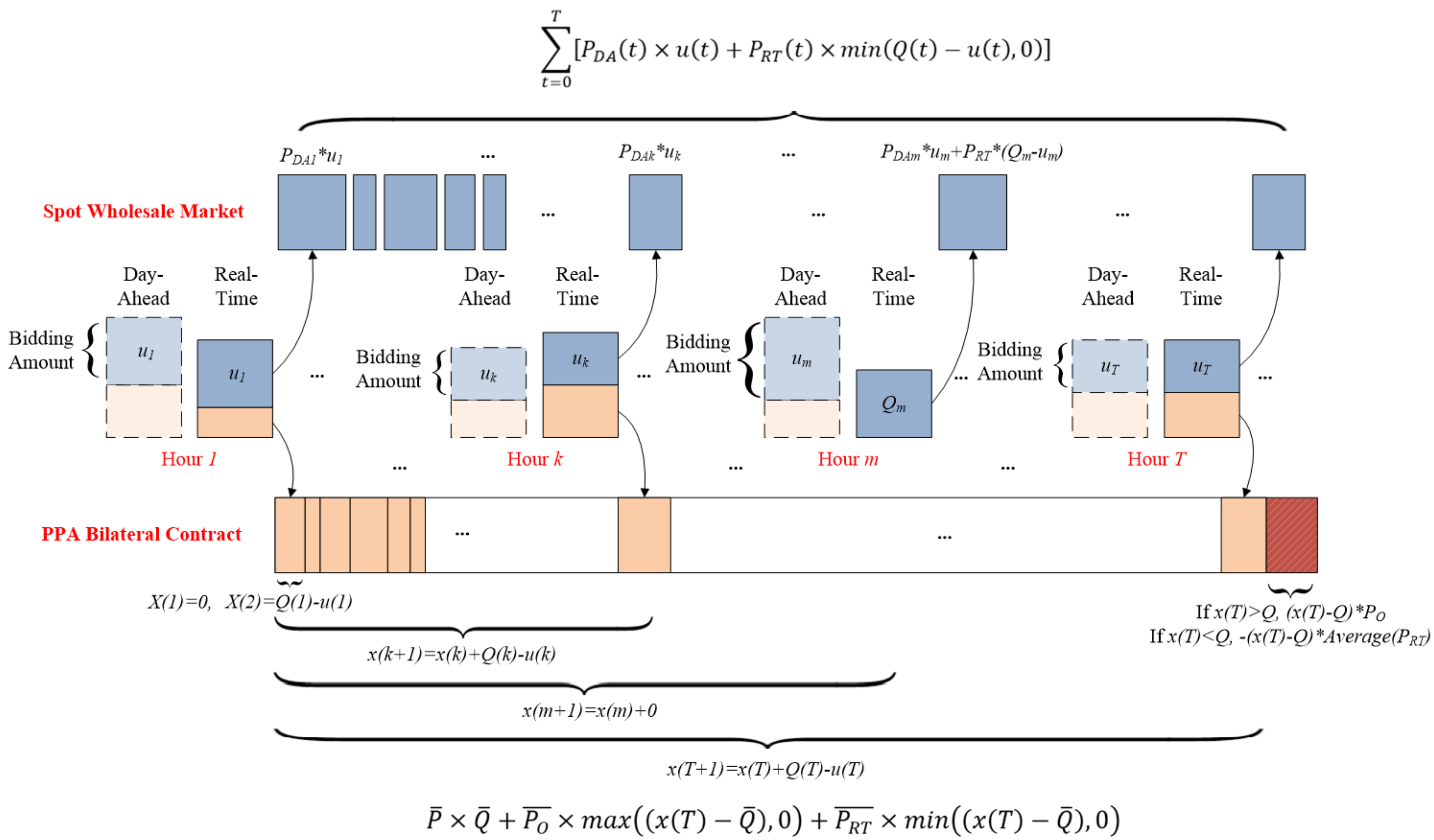


Figure 5-1 Dynamic Offtake Control during the Project Operation

Then for each hour, the remaining electricity will be delivered to the PPA buyer. The settlement with the PPA buyer is different with that of the spot market. Since we assume that the monthly settlement can be converted to a daily settlement, the revenue from the PPA contract will be settled at a daily-bases. The hourly decision for the delivery to the PPA buyer is not independent. Instead, it should consider forward steps till the end of the day. It is a dynamic control problem, with hourly step written as:

$$x(t+1) = x(t) + max\Big(\big(Q(t) - u(t)\big), 0\Big), t = 0, \dots, T-1$$

Where $x(t)$ means at the beginning of the t^{th} hour, how much is the amount of the daily quota that has been fulfilled. At each hour, the amount will be adjusted to that from the previous hour, and the delivery from the actual generation minus the amount that is sold at the spot market.

At the end of the day, the daily revenue from the PPA contract is settled based on the contract terms $\bar{P}, \bar{Q}, \overline{P_O}$. With the contract, the promised quantity $\bar{Q}$ will firstly be settled with price $\bar{P}$, if the actual delivery is more than $\bar{Q}$, then the difference will be settled by the outperformance price $\overline{P_O}$, while if the delivery is not fulfilled, then the wind IPP should pay for a penalty based on the average market price. Therefore, the daily revenue from the PPA contract can be written as:

$$\begin{aligned} &Daily\ Revenue_{PPA} \\ &\quad = \bar{P} \times \bar{Q} + \overline{P_O} \times max\big((x(T) - \bar{Q}), 0\big) + \overline{P_{RT}} \times min\big((x(T) - \bar{Q}), 0\big) \end{aligned} \tag{5-4}$$

With the dynamic transition function and revenue function defined, the general form for the second-level optimization problem can be written as:

$$\begin{aligned} max &\left\{ \sum_{t=0}^{T} [P_{DA}(t) \times u(t) + P_{RT}(t) \times min(Q(t) - u(t), 0)] + \bar{P} \times \bar{Q} + \overline{P_O} \right. \\ &\left. \quad \times max\big((x(T) - \bar{Q}), 0\big) + \left(\frac{1}{T}\sum_{t=0}^{T} P_{RT}(t)\right) \times min\big((x(T) - \bar{Q}), 0\big) \right\} \\ &\quad s.t. \end{aligned} \tag{5-5}$$

$$x(t+1) = x(t) + max\Big(\big(Q(t) - u(t)\big), 0\Big), \qquad t = 0, \dots, T-1 \tag{5-6}$$

5.3.2 *Model Setup and Solving Method*

The model is mathematically hard to solve due to the complicated characteristics of the dynamic control as well as the stochastic parameters. Therefore, we are going to make a simplified assumption of a so-called affine controller to deal with the dynamic process. In that system, the output feedback controller $u(t)$ is assumed to be affine to the system outputs, in the form of $u(t) = \varphi_t\big(x(0), \dots, x(t)\big), t = 1,2 \dots T-1$, in which the functions φ_t are affine. The affine controller design problem is not convex in its original form, but it can be converted through some mathematical transformation into an equivalent convex optimization problem, which makes the problem solvable.

(Skaf and Boyd 2010) firstly present the methodology, and propose to use the classical Q-design procedure to transform the complicated non-convex problem to a solvable convex problem. Detailed proof and mathematical process are summarized in the Appendix B. To deal with the stochastic parameters in the model, a Monte Carlo simulation process needs to be utilized as an approximation for the objectives or the constraints whichever are uncertain in nature (Skaf and Boyd 2010, Boyd and Vandenberghe 2004). Applying the methodology, it is able to get the analytical solution of the second-level problem.

Before applying the methodology of affine controller, we first need to adjust the model so as to transform the formation of the program. Firstly, for the max function in the objective, we add a hard constraint of $u(t) \leq Q(t)$, which will force the bidding amount less than the possible generation amount. Therefore, the *max* part $max\Big(\big(Q(t) - u(t)\big), 0\Big)$ in the system transition function can be approximated as $Q(t) - u(t)$. For the sake of mathematical solvability, it is a stricter constraint than which is assumed previously. Nevertheless, it actually makes sense especially considering that the IPP will try to sell part of the generation to the short-term market, and a stricter self-constraint will be more convincing from the market manger's perspective.

To deal with the *min* function, we define a new variable of $n(T)$, where $n(T) = min(x(T), \bar{Q})$. Then the items in the objective and constraint functions can be substituted as:

$$max\big((x(T) - \bar{Q}), 0\big) = x(T) - n(T)$$

$$min\big((x(T) - \bar{Q}), 0\big) = n(T) - \bar{Q}$$

Since part of the objective is to maximize $n(t)$, then in the constraint, $n(t)$ can be forced to equal the $min(x(T), \bar{Q})$. Meanwhile, another two constraints of $n(T) \leq x(T)$, and $n(T) \leq \bar{Q}$ should be added accordingly. In order to be consistent with the notation of the (Skaf and Boyd 2010), we redefined the notation $W(t) = Q(t)$ as the actual hourly generation amount, which is a stochastic variable in this problem. The final model that is ready for the affine controller programming is expressed as (5-7), where for a daily problem, *T=24*:

$$\begin{aligned} max \Bigg\{ &\sum_{t=1}^{T-1} [P_{DA}(t) \times u(t)] + \bar{P} \times \bar{Q} + \overline{P_O} \times \big(x(T) - n(T)\big) \\ &+ \left(\frac{1}{T-1} \sum_{t=1}^{T-1} P_{RT}(t)\right) \times (n(T) - \bar{Q}) \Bigg\} \end{aligned} \tag{5-7}$$

$$s.t.$$

$$x(t+1) = x(t) + W(t) - u(t), t = 0, \dots, T-1$$

$$u(t) \leq W(t), t = 0, \dots, T-1$$

$$n(T) \leq x(T)$$

$$n(T) \leq \bar{Q}$$

5.3.3 Affine Controller and Simulation

We now apply the affine controller to the model, detailed mathematical proof are summarized in Appendix B. With the detailed parameters *G* and *H* formed, the dynamic system model can be written as:

$$x = Gw + Hu + x_0$$

Where G and H are $(T+1) \times T$ lower triangular matrix:

$$G = \begin{bmatrix} 0 & & & & \\ 1 & 0 & & & \\ 1 & 1 & 0 & & \\ & & & \ddots & \\ & & & & 0 \\ 1 & 1 & \dots & \dots & 1 \end{bmatrix}, H = \begin{bmatrix} 0 & & & & \\ -1 & 0 & & & \\ -1 & -1 & 0 & & \\ & & & \ddots & \\ & & & & 0 \\ -1 & -1 & \dots & \dots & -1 \end{bmatrix}$$

When the causal feedback controller is defined as affine to the outputs from the previous steps, and the Q-design procedure is applied, the decision variables can be further written as:

$$x = (I + HQ)GW + (I + HQ)x_0 + Hr$$

$$u = Q(GW + x_0) + r$$

The decision variable of the problem become Q and r, and the Q is a lower triangular matrix. The problem itself will be transformed to a convex optimization program (Boyd and Vandenberghe 2004) thus can be solved efficiently. Once the problem is solved, as well as the actual generation amount W is given for the specific periods, the bidding amount in the wholesale market $u(t)$ and the corresponding accumulated PPA fulfillment $x(t)$ can be calculated.

Furthermore, since $P_{DA}(t), P_{RT}(t), W(t)$ are all stochastic variables and all having continuous distribution, according to (Skaf and Boyd 2010), we have to approximate the problem by sampling from those parameters' distributions. For sampling M times, the objective function can be replaced by the empirical mean, and the constraints are expanded accordingly. Therefore, the model becomes (5-8):

$$max \frac{1}{M} \sum_{j=1}^{M} \left\{ \sum_{t=0}^{T} \left[P_{DA}^{(j)}(t) \times u^{(j)}(t) \right] + \bar{P} \times \bar{Q} + \overline{P_O} \times \left(x^{(j)}(T) - n^{(j)}(T) \right) + \left(\frac{1}{T} \sum_{t=0}^{T} P_{RT}^{(j)}(t) \right) \times \left(n^{(j)}(T) - \bar{Q} \right) \right\} \tag{5-8}$$

$s.t.$

$$u^{(j)}(t) \le W^{(j)}(t)$$

$$n^{(j)}(T) \le x^{(j)}(T)$$

$$n^{(j)}(T) \le \bar{Q}$$

$$x^{(j)} = (I + HQ)GW^{(j)} + (I + HQ)x_0 + Hr$$

$$u^{(j)} = Q(GW^{(j)} + x_0) + r$$

Substituting x and u to the program, the model becomes a linear stochastic program, with the number of the decision variables as $T(T+1)/2+T+M$. Although the scale of the problem is largely enlarged with the increase of parameter T and M, the problem is still solvable through the commercially available software.

5.4 First Level Long-term PPA Design using Genetic Algorithm (GA)

5.4.1 First Level Optimization Problem

Given the short-term bidding strategy solved with specific contract terms, the first level problem is to iteratively evaluate the contract terms to find the best design for the PPA so that overall profit is optimized. The iterative search procedure can be illustrated through the following Figure 5-2. As shown in the figure, every time the contract term is provided for one PPA contract (first level), the short-term strategy (second level) will be decided based on the contract terms, as well as the estimation of the stochastic variables. The short-term strategy directly decide how the future cash flow will look like, given the sampling from the stochastic variables $W(t)$. Hence the solution of the second level problem can be regarded as a feedback to the first level about the expected revenue. The objective of the first level problem is to iteratively search for a better design of PPA contract terms that could in turn output an overall optimized revenue.

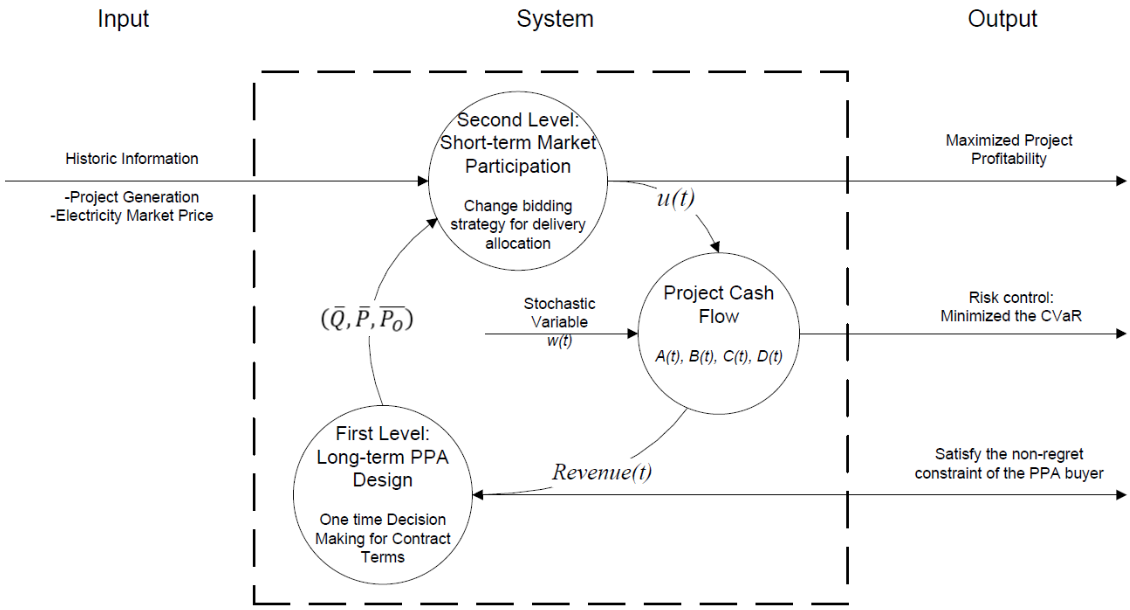


Figure 5-2 Feedback Loop for the First Level Decision Making

Meanwhile, similar to the previous two chapters, two constraints are added in the first level searching. The first one is the CVaR constraint, regarded as the risk control module, and the second one is the chance-constraint, depicting the buyer's no-regret decision making. The first level model can be written as:

$$\max_{\bar{P},\bar{Q},\overline{P_O}} \sum_{t=0}^{T-1}[P_{DA}(t) \times u(t)] + \bar{P} \times \bar{Q} + \overline{P_O} \times max\big((x(T) - \bar{Q}), 0\big) + \left(\frac{1}{T-1}\sum_{t=0}^{T-1} P_{RT}(t)\right) \times min\big((x(T) - \bar{Q}), 0\big) \tag{5-9}$$

$s.t.$

$$\phi_\beta(\bar{Q}, \bar{P}, \overline{P_O}, Q_{RT}, P_{RT}) \leq w \tag{5-10}$$

$$pr\big(Cost_{Buyer}(PPA) - Cost_{Buyer}(Market) \leq 0\big) \geq a \tag{5-11}$$

$$\bar{P} \geq \overline{P_O}$$

$$x = (I + HQ^*)GW + (I + HQ^*)x_0 + Hr^*$$

$$u = Q^*(GW + x_0) + r^*$$

$$Q^*, r^* \; solve\ the\ second\ level\ problem$$

Similar as processed in the last chapter, the (5-9) and (5-10) can be combined as an equivalent objective function:

$$minF_\beta(x,\alpha) - \mu R(x)\,, x \in X, \mu \geq 0, T = 24 \tag{5-12}$$

Where

$$F_\beta(\bar{Q}, \bar{P}, \overline{P_O}, Q_{RT}, P_{RT}, P_{DA}, \alpha)$$

$$= (1-\beta)^{-1} \times \iiint_{Q_{RT}, P_{RT}, P_{DA} \in \mathbb{R}} \{-R(\bar{Q}, \bar{P}, \overline{P_O}) - \alpha\}^+ p(P_{RT}, Q_{RT}, P_{DA}) dQ_{RT} dP_{RT}\, dP_{DA}$$

with

$$\{t\}^+ = \begin{cases} t & when\ t > 0, \\ 0 & when\ t \leq 0. \end{cases}$$

And

$$R(\bar{Q}, \bar{P}, \overline{P_O}) = \sum_{t=0}^{T-1} [P_{DA}(t) \times u(t)] + \bar{P} \times \bar{Q} + \overline{P_O} \times max\big((x(T) - \bar{Q}), 0\big) + \left(\frac{1}{T-1} \sum_{t=0}^{T-1} P_{RT}(t)\right)$$
$$\times\, min\big((x(T) - \bar{Q}), 0\big)$$

The chance constraint (5-11) is the no-regret constraint for the buyer. In specific, for a monthly decision, there is only one constraint that check the buyer's no-regret probability. Let buyer's demand for electricity as Q_{Buyer}, from the PPA contract, the buyer's cost of buying the delivered electricity is

$$\overline{P}\cdot\overline{Q}+\overline{P_O}\cdot max\left(\left(\sum_{t=0}^{T-1}(Q_{RT}-u(t))-\overline{Q}\right),0\right)+\frac{1}{T-1}\sum_{t=0}^{T-1}P_{RT}(t)$$

$$\cdot min\left(\left(\sum_{t=0}^{T-1}(Q_{RT}-u(t))-\overline{Q}\right),0\right)+\frac{1}{T-1}\sum_{t=0}^{T-1}P_{RT}(t)$$

$$\cdot\left[Q_{Buyer}-\left(\sum_{t=0}^{T-1}(Q_{RT}-u(t))\right)\right]$$

And the cost from the market is:

$$\frac{1}{T-1}\sum_{t=0}^{T-1}P_{RT}(t)\cdot Q_{Buyer}$$

Combined, the chance-constraint of buyer's no-regret can be written as (5-13), with which a is set as the confidence level for buyer's decision making.

$$Pr\left(\overline{P}\cdot\overline{Q}+\overline{P_O}\cdot max\left(\left(\sum_{t=0}^{T-1}(Q_{RT}-u(t))-\overline{Q}\right),0\right)+\frac{1}{T-1}\sum_{t=0}^{T-1}P_{RT}(t)\right.$$

$$\cdot min\left(\left(\sum_{t=0}^{T-1}(Q_{RT}-u(t))-\overline{Q}\right),0\right) \tag{5-13}$$

$$\left.-\frac{1}{T-1}\sum_{t=0}^{T-1}\left[P_{RT}(t)\cdot(Q_{RT}-u(t))\right]\leq 0\right)\geq a$$

5.4.2 <u>Genetic Algorithm (GA) and Simulation</u>

Similar to the chapter four, the GA framework can be established to conduct the iterative search. Meanwhile, the simulation procedure is also similar, where the parameter of $P_{DA}(t)$, $P_{rt}(t)$ and $W(t)=Q_{rt}(t)$ are sampled Ω times. Then the objective function (5-12) should be modified as:

$$min\frac{1}{\Omega}\left[\alpha+\frac{1}{\Omega(1-\beta)}\times\sum_{k=1}^{\Omega}\left\{R^{(k)}(x)-\alpha\right\}^{+}-\mu\sum_{k=1}^{\Omega}R^{(k)}(x)\right],x\in X,\mu \geq 0,T=24 \tag{5-14}$$

Where

$$R^{(k)}(\bar{Q},\bar{P},\overline{P_O})=\sum_{t=0}^{T-1}\left[P_{DA}^{(k)}(t)\times u(t)\right]+\bar{P}\times\bar{Q}+\overline{P_O}\times max\left(\left(x^{(k)}(T)-\bar{Q}\right),0\right) + \left(\frac{1}{T-1}\sum_{t=0}^{T-1}P_{RT}^{(k)}(t)\right)\times min\left(\left(x^{(k)}(T)-\bar{Q}\right),0\right) \tag{5-15}$$

The value for the chance constraint is the frequency with which the current solution satisfies the constraints. Let n be the number of random vectors that satisfy the chance constraints. Then with each constraint check, the chance constraints are evaluated as:

$$pr(\cdot)=\frac{n}{\Omega} \tag{5-16}$$

With all the model ready for the algorithm, the GA can be solved with the parameters set up as Table 5-1:

Table 5-1 Parameters for Stochastic GA Programming Setup

Number of Variable, N	4
Size of Population, K=10*N	40
Number of Generation, G=10*K	400
Number of Sampling, Omega	100
Probability of Crossover, Pc	0.7
Probability of Mutation, Pm	0.1

5.5 <u>Case Study for Cape Wind Project</u>

The Cape Wind project will be discussed again in this chapter. The data is to be processed at a daily based, while assuming the market price and wind resource are following the same daily pattern within one month. Therefore, the monthly regression is based on the hourly data collected for the same month. For example, the wind speed for the first hour of the 31 days in January from

2009 to 2012 will be collected to conduct the Weibull regression, and thus form the sampling seed for the first hour of 31 days in January for year 2013. The procedure also apply to the day-ahead and real-time market price, while the distributions are assumed to be normal.

With Ω samples generated, the GA programming are run which calls the affine controller programming as the second level solution, evaluate the chance-constraint and calculate the objective for *pop-size* times. The evolving procedure will be conducted for *Generation* times to find the best PPA contract design which minimize the weight sum of the CVaR and the negative total revenue, and satisfies the buyer's non-regret constraint. Meanwhile, the short-term bidding strategy will also be found through the second level dynamic feedback system. In the end, the model will output a hybrid strategy which enables the project IPP to simultaneously manage the long-term and short-term offtake.

5.5.1 Long-term PPA Solution with Hybrid Strategy

The solution for each month's offtake strategy is separately obtained through 400 *Generations* of GA evolving process. Figure 5-3 takes January as an example and shows the progressing of the solutions through the evolution procedure.

Observation 5.1 With the 400 generations, the decision variables start with a high volatility in the searching area, get stabilized after around the 200th generation, and progressively moving towards the optimized solution from the 280th generation. With the ultimate objective progressing towards minimization, the total revenue is maximized and the CVaR is minimized.

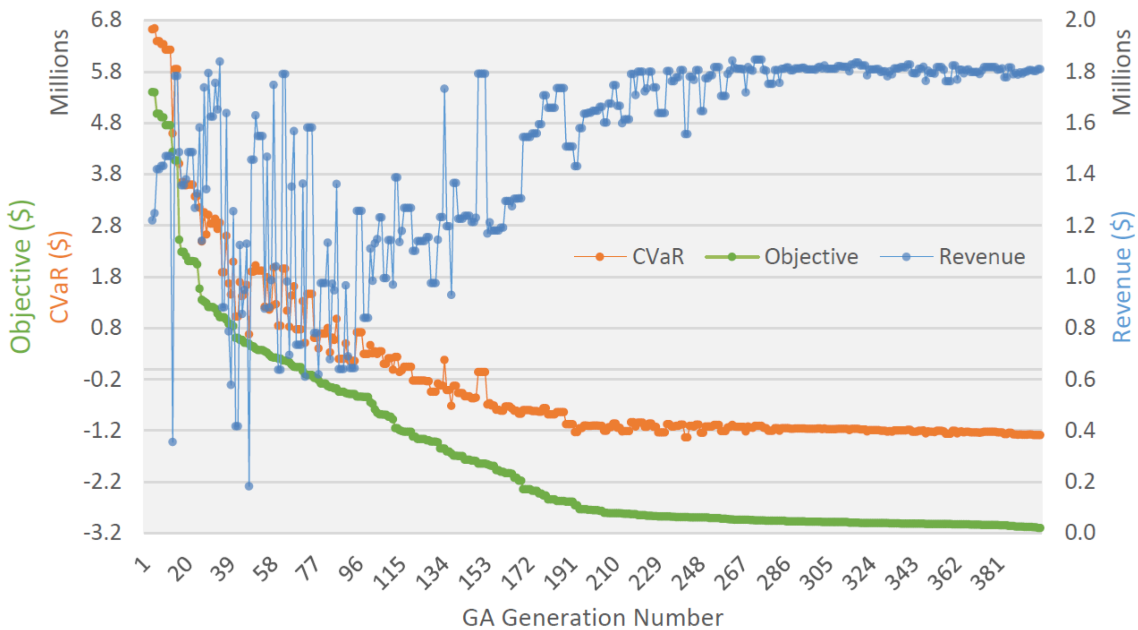


Figure 5-3 Evolution Procedure for GA Programming (Jan)

It is worth notice that the solution obtained from the programming is for the daily PPA. In order to convert to the optimized monthly PPA design for the total project, the electricity delivery quantity should be adjusted with the number of days for the month, the number of wind turbines for the project, as well as the units.

As a result, the contract terms design for the whole year 2013 are summarized as in Table 5-2 and Figure 5-4.

Table 5-2 Solution for PPA Contract Terms

Month	**1**	**2**	**3**	**4**	**5**	**6**
Contract Price ($)	48.64	41.99	40.15	34.83	36.15	38.54
Contract Quantity (kwh)	118	125	102	98.4	82.8	64.8
Contract Outperformance Price ($)	6.35	8.35	2.13	1.19	2.55	2.79
Month	**7**	**8**	**9**	**10**	**11**	**12**
Contract Price ($)	36.12	37.38	40.12	38.65	35.64	41.37
Contract Quantity (kwh)	67.3	68.4	92.4	122	129	136
Contract Outperformance Price ($)	3.54	3.32	4.91	1.66	2.24	3.06

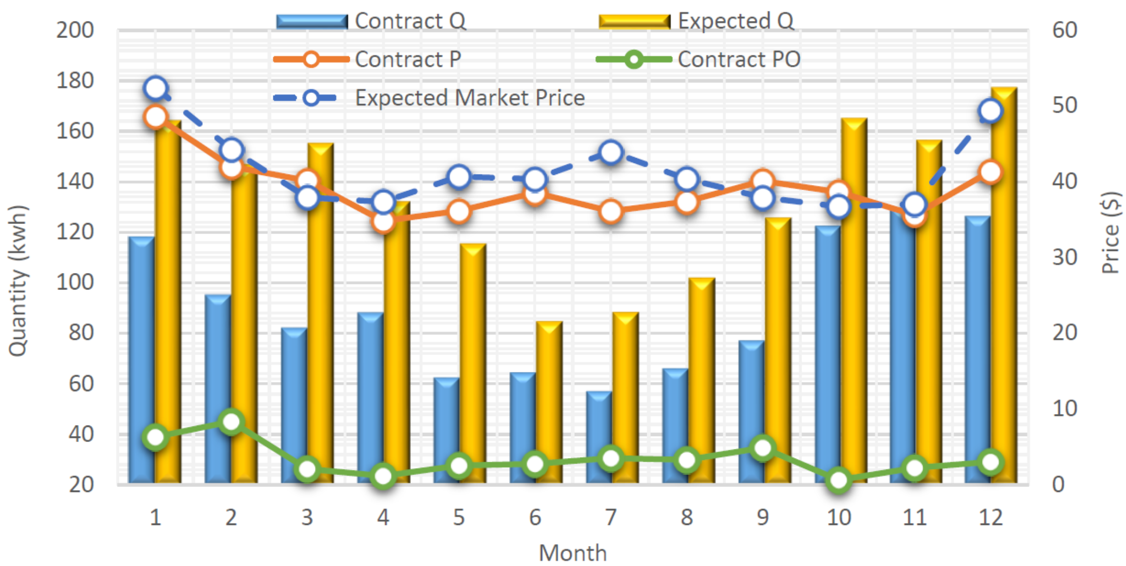


Figure 5-4 Long-term Decision for PPA Contract

Observation 5.2 Different with the single PPA strategy, with the hybrid strategy, both the contract price and the contract delivery amount are signed as smaller than the expected market parameters.

As shown in the figure, the wind IPPs only takeoff part of their generation capacity using long-term PPA contract, so that they can use the remaining capacity to take advantage of the short-term wholesale market offtake. The proportion of the contract amount over the expected generation capacity is in average 75%, with the range of [66%, 85%]. That means about one-quarter of the generation capacity are expected to be sold through the wholesale market.

Meanwhile, in order to obtain the flexibility of allocation between the two types of strategies, the wind IPP is willing to sign lower contract price for PPA buyer than expected market price. Furthermore, the outperformance price is very small since the IPP has high flexibility to sell the redundant amount to the market but not to the PPA buyer. The lower outperformance price can be treated as a good negotiating point when the buyer is considering their no-regret possibilities.

Observation 5.3 As to the profit sharing between the IPP and the buyer, better contract design from the IPP's perspective means that the buyer is pushed to their threshold for accepting the contract.

As shown in Figure 5-5 taking January as the example, with the genetic searching evolving, the no-regret probability starts with high volatility and remains in high values. When the GA programming starts to progress to the optimization after around 300th generation, the no-regret probability is pushed towards the threshold 50%. Similar to the single PPA design, the threshold of the chance constraint is an important negotiation point as a benefit sharing parameter.

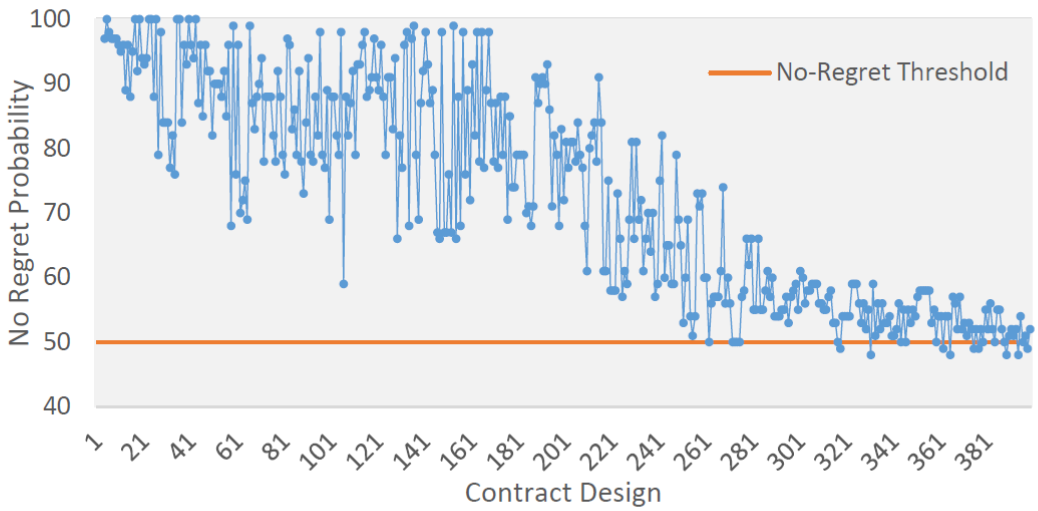


Figure 5-5 GA Result for No-regret Probability (Jan.)

5.5.2 *Short-term Bidding with Hybrid Strategy*

The short-term dynamic control strategy is solved together with the long-term strategy simultaneously. As a result, with the optimized contract terms found, the optimal short-term bidding strategy are solved through the affine controller optimization problem. It is worth mention that the second level problem does not provide a fixed bidding amount $u(t)$, instead, it solves an optimal so-called close-loop matrix Q and r. So that given the actual input of the stochastic variable W, the bidding amount $u(t)$ and the PPA delivery $x(t)$ can be calculated accordingly. Without knowing the actual generation amount, we first refer to the 100 samples from the sampling seeds to check the strategy and its expected results, then actual performance of the strategy design will be discussed using out-of-sample analysis.

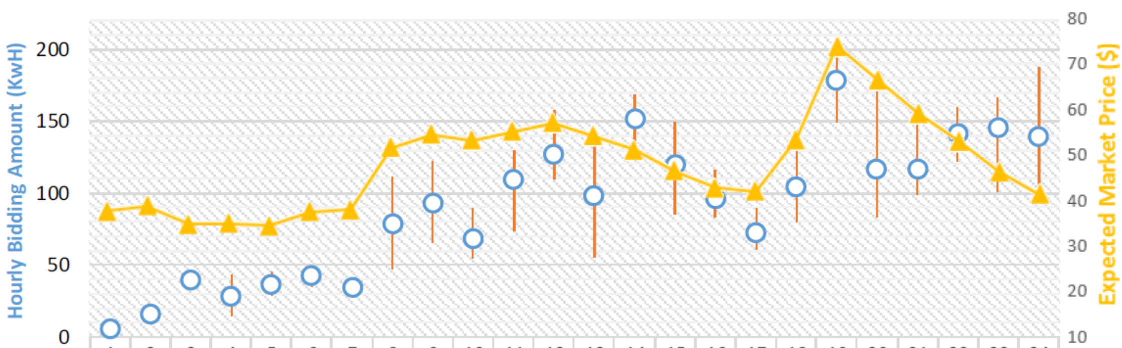
We respectively gather five best and five worst strategy designs based on their objective values. Figure 5-6 shows the expected mean and variance of the bidding amount, and demonstrates the effectiveness of the strategy design.

Observation 5.4 With better strategy design, the short-term bidding is able to capture the trend of the market price so as to take advantage of the price volatility. Meanwhile, better strategies are more stable and robust, which are not easily influenced by the stochastic variable input.

As shown in the figure, the bidding amount of the five best strategies have higher covariance with the expected market price. As a result, the electricity allocation to the wholesale market could bring higher revenue. On the contrary, the worse strategies are more random in terms of the bidding amount, which is not relevant to the expected market price. Therefore, even with the same total bidding amount, the revenue are expected to be lower.

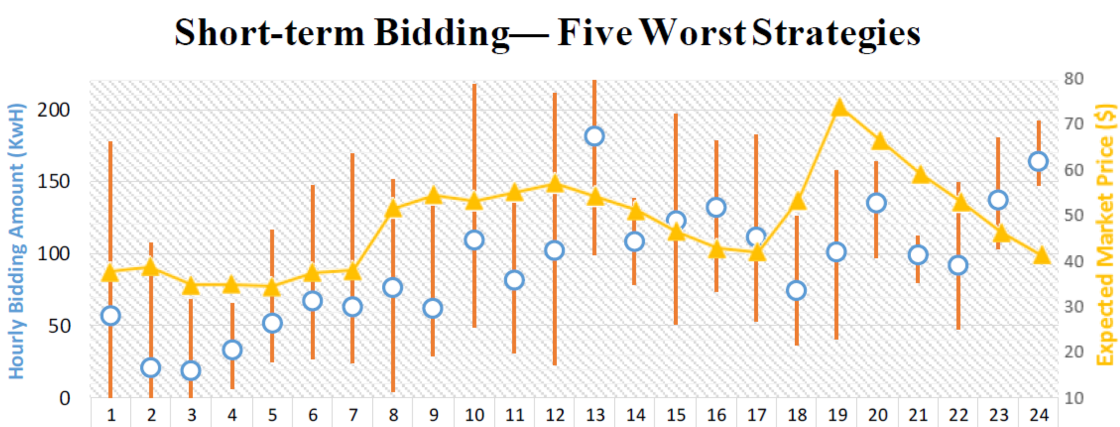
The robustness of the strategy can be reflected from the variance of the bidding amount. A better strategy design takes the stochasticity into consideration when the decision is made, while during the operation phase, the actual execution of the strategy is under better control. This can be illustrated from the variance comparison in the figure.

Short-term Bidding— Five Best Strategies



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
High	7.43	19.9	45.9	43.2	44.8	48.7	41.5	111	122	89.8	129	158	135	169	149	117	89.8	136	204	171	159	160	167	188
Low	3.81	11.9	33	14.6	28.7	34.8	28.8	47.3	65.8	54.7	74	110	55.9	133	84.9	83.2	60.9	80	149	83.3	98.7	122	101	106
Mean	5.67	16.1	39.9	27.8	36.2	42.3	34.8	78.6	92.6	68.4	109	127	98.7	152	120	96.2	72.8	105	178	116	117	142	146	139

Time



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
High	177	108	68.1	65.6	117	148	169	151	141	217	137	211	268	138	197	178	183	126	158	164	113	150	181	192
Low	0	0	0.38	6.67	24.9	26.8	24.4	4.61	29.4	48.6	31.5	23	99.1	78.3	50.5	74	52.6	36.9	40.3	96.8	79.8	47.9	103	148
Mean	56.9	21.6	19.2	33.4	51.6	67.5	62.7	76.7	61.9	110	81.9	102	182	108	123	132	112	74.1	101	135	99.7	91.6	137	164

Time

Figure 5-6 Different Strategy Design for Short-term Bidding

Similarly, continuous PPA delivery amount can also be calculated given the close-loop matrix Q and r solved through the program. With the 100 samples, the expected mean of the hourly and accumulated electricity delivery to the PPA buyer for January are shown in Figure 5-7.

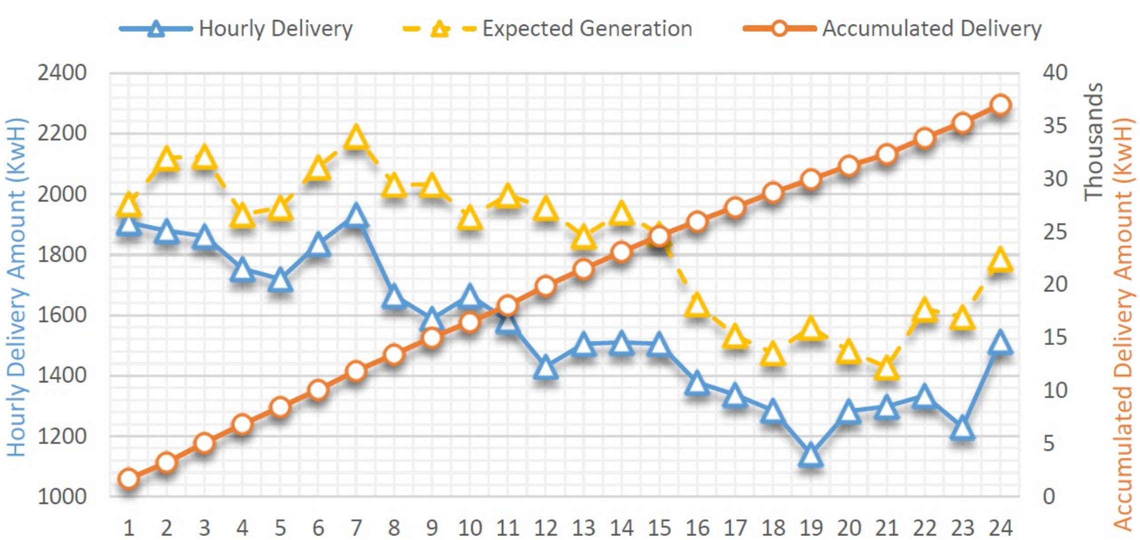


Figure 5-7 Hourly and Accumulated Electricity Delivery to PPA Buyer (Jan.)

Observation 5.4 The IPP always choose to deliver less than the expected generation, so as to be conservative to avoid paying for the penalty, or getting paid for the outperformance, which is much less than the market price.

Unlike the single PPA contract when the redundant electricity have to be sold with a lower outperformance price, the hybrid strategy enables the IPP to better allocate the generation between the two options thus maximize the revenue. In this sense, the PPA offtake of the hybrid mechanism has realized the "storage" role that provides complementary buffers to the short-term offtake.

With both offtakes amount allocated, the expected mean of the total revenue and CVaR can be calculated associated with the 100 samples. Figure 5-8, Table 5-3 and Table 5-4 summarize the allocation of the revenues and CVaR from the two offtake channels.

Observation 5.5 The long-term and short-term offtake are expected to contribute differently in terms of the revenue and CVaR, thus balancing the trade-off between revenue and risk.

As shown in Figure 5-8, the total monthly revenue follow the similar seasonal trend as discussed in the previous two chapters. As a result, the expected annual revenue is \$7.13E+07, of which the revenue from the long-term offtake is expected to be \$5.06E+07, accounting for 71%, and that from the short-term offtake is expected to be \$2.08E+07, accounting for 29%. This ratio corresponds with the delivery amount allocation, which is 75% to 25%, due to the higher unit revenue from the wholesale market.

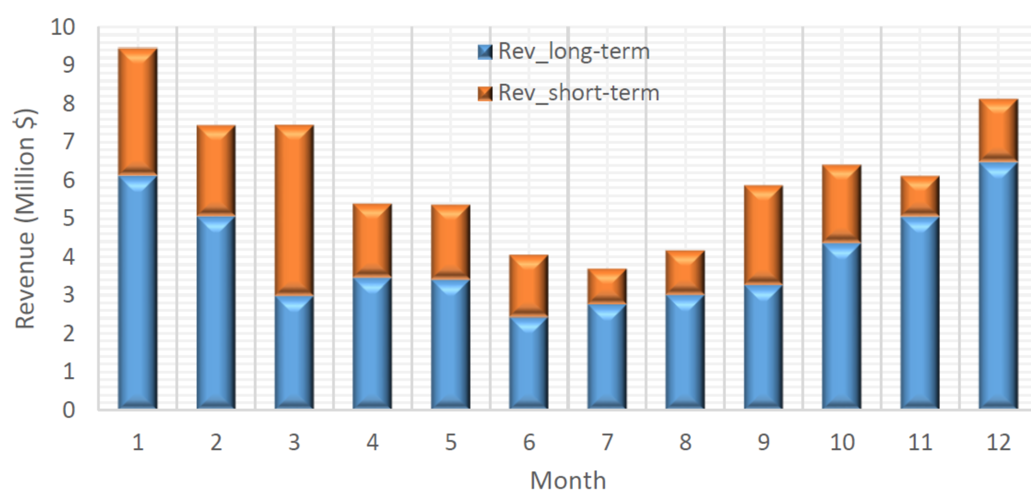


Figure 5-8 Expected Monthly Revenue Allocation

As to the revenue cash flow risks, the CVaR for the long-term offtake is kept at a low level, which is favored due to its low volatility as promised by the contract terms. On the other hand, the CVaR from the wholesale market is high as expected due to the uncertainty of the market price. In specific, the relative CVaR for the short-term offtake, long-term offtake and total revenue, which is defined as the ratio of the CVaR divided by the expected revenue, are respectively -15%, -59%, and -47%. Thus the CVaR for the total revenue is the balance between the two offtake strategies.

Table 5-3 Monthly CVaR for Offtake Revenue Allocation

Month	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**
Short-term Offtake	-2.54E+05	-1.60E+05	-2.13E+05	-1.10E+05	-1.41E+05	-1.16E+05
Long-term Offtake	-2.51E+06	-4.98E+06	-5.84E+06	-2.65E+06	-2.85E+06	-1.79E+06
Total Offtake	-2.82E+06	-5.22E+06	-6.12E+06	-2.82E+06	-3.02E+06	-1.94E+06
Month	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
Short-term Offtake	-9.69E+04	-1.57E+05	-1.00E+05	-2.08E+05	-1.69E+05	-3.92E+05
Long-term Offtake	-1.53E+06	-1.92E+06	-3.13E+06	-2.59E+06	-2.02E+06	-4.33E+06
Total Offtake	-1.70E+06	-2.11E+06	-3.32E+06	-2.86E+06	-2.25E+06	-4.94E+06

Table 5-4 CVaR for Annual and Monthly Revenue

	Mean of Monthly CVaR	**Annual CVaR**	**Relative CVaR (Annual)**
Short-term Offtake	-1.65E+05	-3.09E+06	-15%
Long-term Offtake	-3.44E+06	-4.14E+07	-59%
Total Offtake	-3.66E+06	-3.47E+07	-47%

5.5.3 Out-of-Sample Analysis——Performance of the Hybrid Offtake Strategy

With the optimized strategies solved, we take the real data from the year 2013 to conduct an out-of-sample analysis, so as to validate the effectiveness and efficiency of the model.

Observation 5.6 With the hybrid strategy, the wind IPP is more resilient to deal with the volatility of the stochastic parameters.

Figure 5-9 summarize the realization of some parameters comparing with the expected value. As shown in the figure, with the option of delivering to the wholesale market, the actual delivery can be kept close to the promised contract quantity, so as to avoid losses due to the underperformance or outperformance. The deviations of the delivery comparing with the contract amount are in the small range of [10%, 11%].

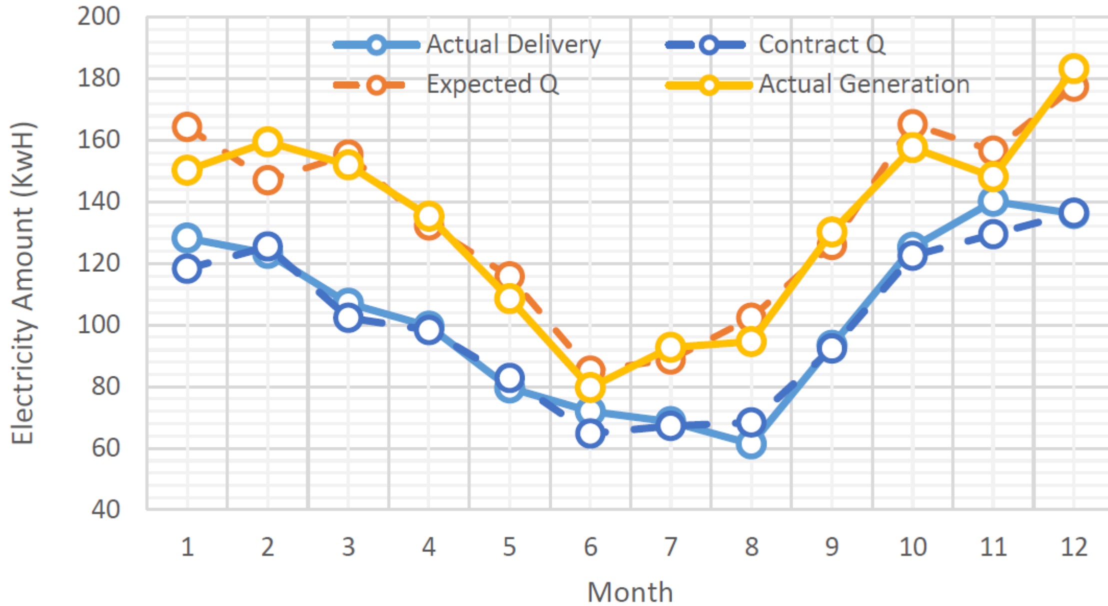


Figure 5-9 Actual Parameter V.S. Expected Value of Year 2013

As a result, the revenue from the long-term offtake, the PPA contract does not deviate much from the expected value. As shown in the Figure 5-10, most of the volatilities are digested through the short-term offtake.

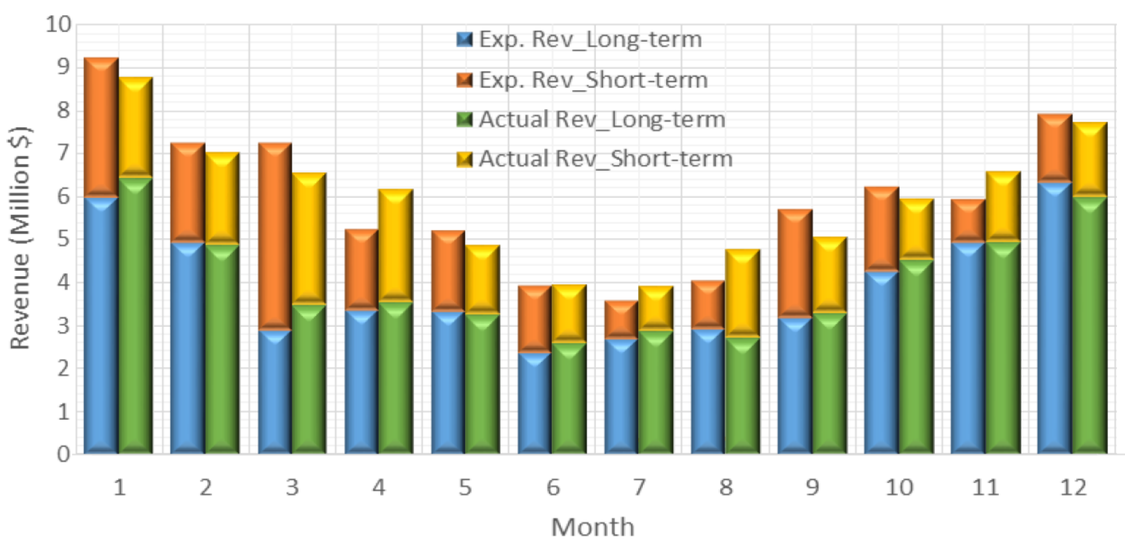


Figure 5-10 Actual Revenue V.S. Expected Revenue of Year 2013

Observation 5.7 As to the profit sharing, since the hybrid strategy enables the IPP to control the long-term delivery amount very close as promised in the contract, the buyer's savings from the PPA mainly rely on the difference of the actual electricity price and the contract price. The uncertain part of the IPP's revenue is also associated with the volatility market price.

As shown in the Figure 5-11, for the months that the actual market price is higher than the contract price, the buyer's saving is obvious, while the buyer also takes risks for the months that the actual price is lower. Overall, the buyer could expected a stable unit cost from the contract, while the savings depend on the accuracy of market estimation when the contract is signed.

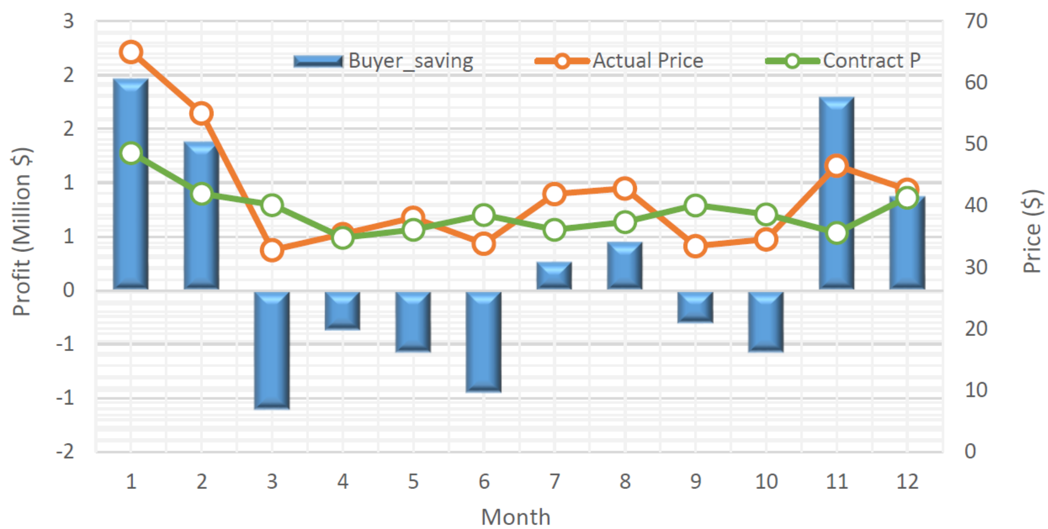
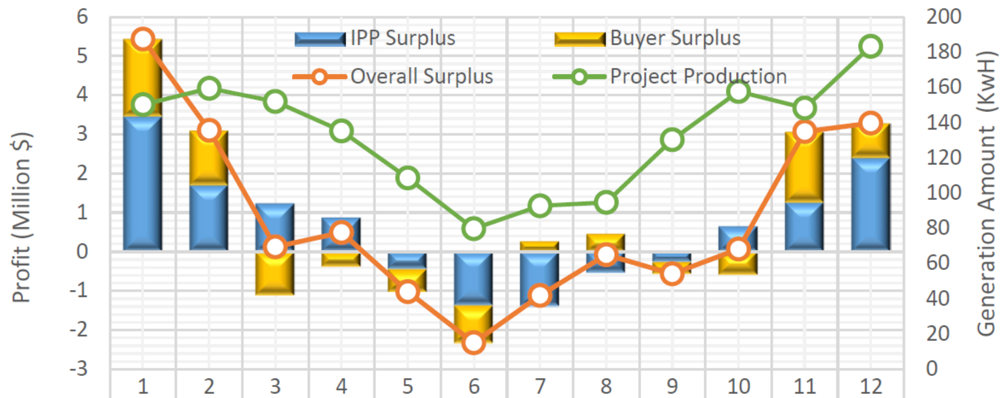


Figure 5-11 PPA Buyer's Monthly Profit

Meanwhile, from the IPP's perspective, since the delivery and price for the long-term offtake is pretty certain, the main uncertainty of the revenue still comes from the short-term offtake. However, since the short-term strategy only accounts about 25% of the total offtake, the volatility of the total cash flow are still under control.

Assuming the project capital cost is with 30% debt at 8.0% interest rate, 50% tax equity at 8.5% cost and 20% common equity at 12% cost, the average subsidized cost for the wind project is approximate \$40/Mwh (LAZARD 2011), then the annual cost for the Cape Wind project for year 2013 is about $\$6.37\times10^{7}$. Since the cost is mainly capital cost, we assume the cost will be evenly distributed throughout every month, hence the monthly cost will be $\$5.57 \times 10^6$. Combining the revenue and the cost, we can get both parties' and overall surplus, as shown in Figure 5-12.



Month	1	2	3	4	5	6	7	8	9	10	11	12
Buyer Surplus	1.97	1.39	-1.11	-0.38	-0.58	-0.96	0.27	0.46	-0.31	-0.58	1.81	0.88
IPP Surplus	3.46	1.71	1.24	0.87	-0.44	-1.37	-1.39	-0.54	-0.25	0.65	1.26	2.40
Overall Surplus	5.43	3.10	0.12	0.49	-1.02	-2.33	-1.12	-0.08	-0.56	0.07	3.07	3.28
Project Production	150	159	152	135	109	80	93	95	130	158	148	183

Figure 5-12 Surplus for Different Stakeholders of the Project (Year 2013)

Observation 5.8 The IPP and the PPA buyer are essentially sharing the benefits and surpluses. The total surplus shows a significant seasonal trend that is associated with the project's generation.

Although there are several months in which the project itself, as well as the overall benefit, is in red, the total investment return for the whole year is positive and as high as 12.05% (Table 5-5).

Table 5-5 Annual Surplus Sharing and Investment Return for the Project (2013)

Overall Surplus ($)	**Buyer Surplus ($)**	**IPP Surplus ($)**	**IPP Cost ($)**	**Investment Return (before Tax)**
1.05E+07	2.87E+06	7.68E+06	6.37E+07	12.05%

5.6 <u>Performance Comparison — Short-term, Long-term and Hybrid</u>

With all three strategies defined and solved through different methodologies and program setup, the last task is to compare the performance of these three in terms of their expected revenue and risks, as well as their actual performance through the out-of-sample analysis. In the chapter three to five, since the three strategies are all applied to the Cape Wind project and sharing the same sampling seeds, we assume that the results are comparable. Therefore, we are going to re-organize the calculation and statistical analysis throughout the three chapters and draw corresponding observations.

In specific, we are going to compare the results of the proposed short-term and hybrid strategies, and as to the long-term strategy, we are going to take both S2 and S3 considering the different preferences from the project developer as well as the industrial policies.

5.6.1 *Expected Annual Revenue and Cash Flow Volatility*

Observation 5.9 As summarized in the Figure *5-13*, short-term strategy obtains the highest expected annual revenue, while long-term strategy get the best performance of controlling the cash flow volatility, in term of the lowest annual CVaR. The hybrid strategy, as expected, balances the revenue and the risk.

We use a metric called normalized annual CVaR, defined as $\left|\frac{annual\ CVaR}{annual\ Revenue}\right|\%$, to intuitively represent the expected shape of future revenue. For each strategy, the normalized annual CVaR are respectively 19%, 82%, 84%, and 49%.

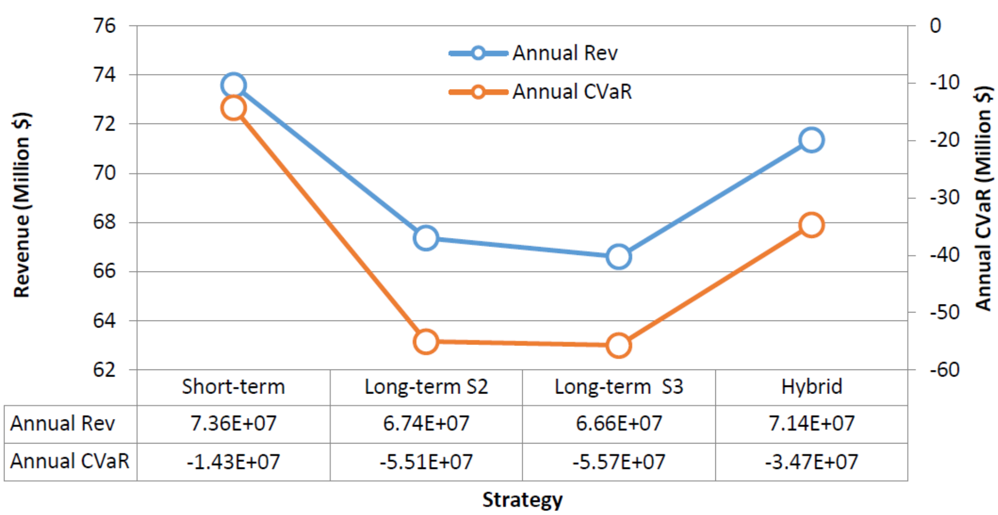


Figure 5-13 Annual Revenue and CVaR for Strategy Comparison

Observation 5.10 Different risk attitude of the project owner will lead to different selection for the offtake strategies. Risk averse IPPs would favor long-term PPA offtake, risk taker will go for short-term offtake, while risk neutral IPPs would choose the hybrid offtake.

Figure 5-14 demonstrate the efficient frontier of the weighted value for revenue minus CVaR with regard to the wind IPP's risk attitude. The risk attitude is defined as the weight of the owner's favor for annual revenue. As shown in the figure, from ratio changing from 3:1 to 20:1, the IPP will change from long-term offtake to hybrid offtake, to short-term offtake. For ratios that are less than 3:1, all IPPs will choose long-term strategy, and some will favor long-term S3 to S2.

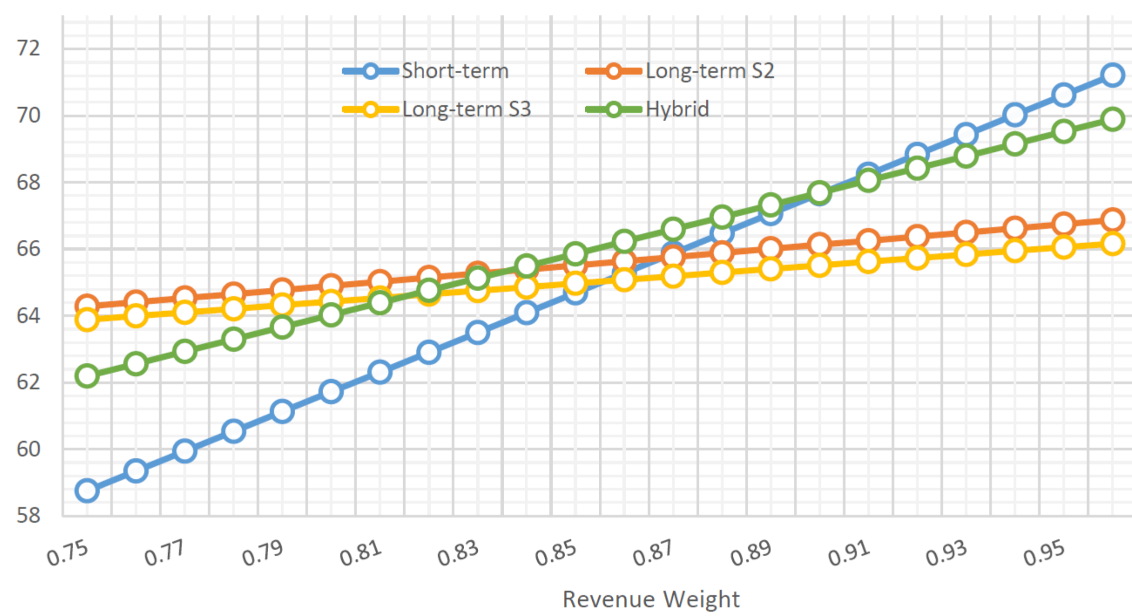


Figure 5-14 Efficient Frontier of Wind IPPs' Strategy Selection

5.6.2 <u>Expected Monthly Revenue and Cash Flow Volatility</u>

Monthly revenue and cash flow volatility are of more interest when the project finance is evaluated based on monthly payback. For different strategies, the expected monthly cash flow and CVaR are plotted in Figure 5-15.

Observation 5.11 Similar to the annual trend, the hybrid strategy acts a trade-off both for the monthly revenue and CVaR. The short-term offtake generate the highest monthly revenue, but also embrace the highest risks. It is worth notice that although the monthly revenue for the two long-term strategies S1 and S3 are similar, the risk control from the S3 are much better than the S1. In this sense, if the IPP is going for the long-term strategy, S3 is more favored.

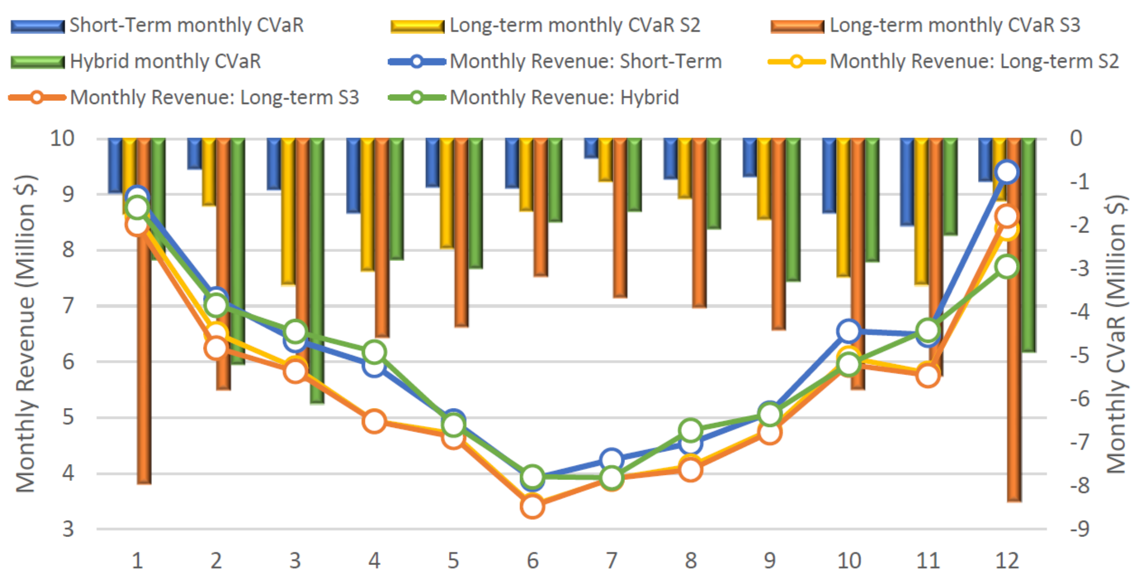


Figure 5-15 Expected Monthly Revenue and CVaR for Different Strategies

5.6.3 *Out-of-Sample for Actual Performance*

When applying the 2013 real data to the three strategies, the actual revenue are realized, which will be used to evaluate project owner's profit and rate of return. Meanwhile, for the long-term and hybrid strategy, the benefit sharing between the two parties of the contract will also be revealed.

Table 5-6 Actual Revenue and Benefit Sharing with Different Strategies (Year 2013)

	Short-term	Long-term S2	Long-term S3	Hybrid
Actual Revenue ($)	7.36E+07	6.6547E+07	6.56E+07	7.14E+07
IPP Surplus ($)	9.82E+06	2.87E+06	1.93E+06	7.68E+06
Rate of Return	15.56%	4.51%	3.03%	12.05%
Buyer's Surplus ($)		1.07E+06	2.01E+06	2.87E+06
Overall Surplus ($)		3.94E+06	3.94E+06	1.05E+07

Observation 5.12 Although the long-term strategy control the volatility in the planning phase, the amount of profit that it sacrifices is significant, which is even less than one-third of the possible

profit capacity from the short-term strategy (Table 5-6). When the long-term offtake strategy is utilized, there need some extra benefit to make the contract attractive.

All these results explain why the long-term contracts are more favored for their risk control mechanism, while the project cannot realize self-sustainment purely through the contracts but should rely on some external support. In practice, For example, tax equity holder are willing to invest so that they can take advantage of the tax credit and accelerated depreciation; investment equity holders are negotiating about the ownership of the Renewable Energy Credits (RECs).

The hybrid strategy, on the other hand, is expected to balance the advantage of the short-term and the long-term strategy. Meanwhile, it is also eligible for the external benefits that long-term strategy has, which makes it more attractive.

*5.7 **Conclusions***

In this chapter, we propose a new hybrid offtake strategy for wind energy projects which integrates the short-term wholesale market offtake and the long-term PPA contract offtake, as discussed in the previous two chapters. The essential idea is to find a trade-off between the revenue and the risks through the flexibility to allocate the generation capacity between the long-term and short-term offtake.

The challenge to design such a strategy is the different time scale and settlement procedure between the two channels. An integrated methodology needs to be identified to completely address the interdependent relationship and to solve the two strategies simultaneously.

A two-level stochastic optimization model was developed in this chapter, with which the first level (long-term contract design) incorporates the solutions from the second level (short-term bidding strategy) as a feedback, and the second level treats the first level as a leader and makes the decision as a follower. In the end, with iterative dynamic feedback searching, the strategies for both channels are solved simultaneously.

With the solutions verified by the 100 samples, the characteristics and advantages of the hybrid strategy can be summarized as the following threefold:

1. The hybrid strategy realizes the balance between the revenue and the risk control. It helps to maintain a high level of fulfillment for the PPA contract, thus is able to avoid underperformance penalties, and maintain steady cash flow with smaller volatility. Meanwhile, with less contracted generation capacity, the wind IPPs are entitled with much more flexibility to allocate the remaining generation to the wholesale market, thus maximize the overall revenue.
2. The flexibility of allocating the generations can be regarded as options when IPPs are making decisions on *wait-and-see* scenarios. It largely enhances the IPPs' capability of capturing the wholesale market volatility and avoiding unnecessary delivery to the PPA due to outperformance.
3. With the hybrid strategy, wind IPPs sign off less amount of promised delivery to the long-term PPA contract. The two offtake channels can then be treated as complementary buffers to each other, thus both the PPA contract buyer and the wholesale market manager can expect a higher reliability from the wind project.

The out-of-sample analysis justifies the model building and the observations. It also verifies the effectiveness of the strategy in terms of the benefit and risk sharing outcome among different stakeholders.

In the end, the pros and cons of the three different offtake strategies are discussed. The hybrid offtake strategy combines the advantages from both the other two strategies and provides the trade-off between the revenue and risks. Meanwhile, a well-designed strategy enhances the surplus of both parties within the long-term relationship, thus obtains a higher overall value for the supply chain.

Chapter 6. Summaries and Conclusions

This dissertation proposes three offtake strategies for wind project development in the U.S., namely short-term, long-term, and hybrid strategies. After an introduction to research background and early literatures in the first two chapters, chapter three and chapter four developed modified short-term and long-term offtake models that incorporate risk control modules and stakeholder relationship management into the decision making process. Chapter five, furthermore, proposed a new hybrid offtake approach that integrates the advantages of existing strategies and achieve an optimal balance between revenue maximization and risk minimization.

This research provides insights on the analysis method and systematic design for offtake strategies in a wind energy project development. The study offers a better understanding of managing the uncertainty of wind resource and power market, therefore allows project developers to improve project revenue streams, effectively reduce the levelized Cost of Energy (LCOE), and ultimately enhance the viability of renewable energy projects.

6.1 Summaries of Proposed Methodologies and Results

Different methodologies and problem solving techniques are applied in each chapter.

The short-term offtake deals with the decision making in the electricity wholesale spot market. In order to incorporate the minimization for the revenue cash flow volatility, a metric called Conditional Value-at-Risk (CVaR) is introduced. With the mathematical transformation by defining a so-called F function, the short-term offtake problem is then expressed as a stochastic linear programming and is solved by commercially available software.

The long-term offtake strategy considers a multi-year bilateral contract called Power Purchase Agreement (PPA) with electricity buyers. A stochastic programming model is proposed to optimize the strategy, maximize the discounted cash flow and minimize the CVaR of the revenue flows. Meanwhile, in order to incorporate the buyer's no-regret threshold, a chance-constraint related to the market value of the electricity production is embedded as a stakeholder relationship management and negotiation module. The heuristic Genetic Algorithm is then used to deal with the complicated solving procedure.

Finally, the hybrid offtake strategy is discussed endowing the project developer with more flexibility to balance and hedge against the volatile factors during the project operation. A two-level stochastic programming is proposed to combine the decision making for long-term and short-term as an integrated model. In the model, the first level is to optimize the long-term contract design as a *here-and-now* decision making, while the second level deals with the dynamic bidding strategy in the wholesale market as a *wait-and-see* decision during the project operation. A feedback loop is the key of the two-level optimization, where the first level incorporates the solutions from the second level as a feedback, and the second level treats the first level as a leader and makes the decision as a follower. With an affine controller for the second level and GA for the first level, the solutions for the allocation between the two offtake channels can be solved simultaneously.

As observed from the discussion part of each chapters, the proposed modification for the short-term and long-term strategy enhance the expected revenue and risk control for the project, on top of the traditional method. The hybrid model further improve the performance of the project not only by balancing the two options, but also by realizing better benefit and risk sharing through the contract design. The out-of-sample analysis of the actual Cape Wind project also justifies the hypothesis that we made in the assumption, the model building and the analysis throughout the dissertation.

6.2 Contribution to the Body of Knowledge and Practical Application

The topic of this dissertation is inspired by industrial practical needs and academia knowledge gaps about offtake strategies for wind energy projects, especially considering the uncertain environment where the project is proposed, designed, financed and operated. It is expected that the framework and the methodologies proposed in the dissertation will provide wind project developers with systematic and quantitative approaches for developing their offtake strategies.

Two issues are mainly addressed: (1) what are good offtake strategies for wind projects, and (2) how to design and execute the strategies considering the uncertainties. The methodologies proposed will help to estimate the value of the project more accurately, to improve the long-term profit, and to better control the revenue flow risks. The topic covers the subjects of project risk management, game theory, operations research, contract engineering, and system control.

Given the unique nature of wind projects, it is a significant challenge to address the stochastic nature of the project operation and offtake environment. In our model, special attention is paid to the uncertainty with the future cash flow in terms of the volatility of the wind resource and the unstable electricity market price. In particular, the risk management fully takes the stochastic nature into consideration through controlling the Conditional Value-at-Risk (CVaR) of the cash flow.

Furthermore, this research innovatively proposes a hybrid strategy combining short-term decision making and long-term contract design. With the specific two-level stochastic optimization model, the project developers are provided with more flexibility allocating their production and will be able to better balance the potential opportunities, and hedge the possible risks.

Although this research primarily focuses on the wind project, the strategies and methodology proposed can be extended to cover other similar renewable energy projects, such as solar PV, concentrated solar power (CSP), and hydro power projects. The PPA design and the two-level feedback strategy design can also be applied in a broader set of project types in terms of the contract negotiation and stakeholder relationship management.

6.3 Limitations and Future Researches

There are several directions that the research can be improved and future researches can be conducted.

Firstly, we make some simplification of the project cost, so that the main objective we consider for the offtake strategy is to deal with the revenue, instead of profit. We assume the variable cost for the project as zero considering the net zero fuel use, and only consider the capital cost as a monthly constant. If the actual operation cost could be better estimated and included in the future cash flow, the profit streams will be more accurately evaluated and fit more to the reality.

Secondly, we only consider the unsubsidized situation, and also exclude the potential revenue from the REC market. However, most of the renewable projects are eligible for tax credit or some federal/state credit program. In fact, many project investors are only interested in the renewable energy project when they can take advantage of these programs. Therefore, a potential interesting topic associated with this will be the public policy design and their impact on the project offtake strategies.

Last but not least, the accuracy of the estimation for the stochastic variables is always a technical challenge for prediction models. In our discussion, we only assume the most basic Weibull distribution for wind speed and normal distribution for market prices. Another improvement of the model and a future direction to apply the model into practice will be to incorporate more advanced estimation technologies and to implement real-time self-adaption.

Appendix A Conditional Value-at-Risk (CVaR) (Adapted from (Rockafellar and Uryasev 2000))

Figure A-1 illustrates the definition for β-VaR and β-CVaR, on a hypothesis loss function distribution.

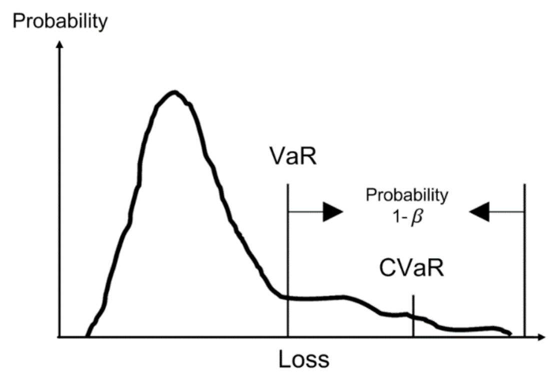


Figure A-1 Illustration for Definition of β-VaR and β-CVaR

By definition, VaR is the percentile of the loss distribution, i.e., with a specified confidence level β. The β-VaR is the lowest amount α such that, with probability β, the loss is less or equal to α. With $f(x,y)$ defined as the loss function, the probability of $f(x,y)$ not exceeding a threshold α is given by:

$$\Psi(x,\alpha) = \int_{f(x,y)\leq\alpha} p(y)dy$$

Therefore β-VaR is expressed as:

$$\alpha_\beta(x) = min\{\alpha \in R: \Psi(x,\alpha) \geq \beta\} \tag{A-1}$$

β- Conditional Value-at-Risk (β-CVaR), on the other hand, is defined as the conditional expectation of the loss associated with x relative to that loss being $\alpha_\beta(x)$ or greater, which is to be expressed as:

$$\phi_\beta(x) = (1-\beta)^{-1} \times \int_{f(x,y)\geq\alpha_\beta(x)} f(x,y)p(\mathrm{y})dy \tag{A-2}$$

The key to the approach to quantitatively evaluate β-CVaR of the underlining asset is to define the function of F_β as follows:

$$F_\beta(x,\alpha) = \alpha + (1-\beta)^{-1} \times \int_{f(x,y)\geq\alpha_\beta(x)} [f(x,y)-\alpha]^+ p(\mathrm{y})dy \tag{A-3}$$

It has been approved that minimizing the β-CVaR of the loss associated with x over all $x \in X$ is equivalent to minimizing $F_\beta(x,\alpha)$ over all $(x,\alpha) \in X \times \mathbb{R}$, in the sense that

$$min\phi_\beta(x) = minF_\beta(x,\alpha) \tag{A-4}$$

Meanwhile, the integral in the definition (A-3) can be approximated by sampling the probability distribution of y according to its density $p(y)$. If the sampling generates a collection of vectors $y_1, y_2, \dots y_q$, then the corresponding approximation to $F_\beta(x,\alpha)$ is

$$\tilde{F}_\beta(x,\alpha) = \alpha + \frac{1}{q(1-\beta)} \times \sum_{k=1}^{q} [f(x,y_k)-\alpha]^+ \tag{A-5}$$

Appendix B Affine Controller (Adapted from (Skaf and Boyd 2010))

Consider a discrete-time linear time-varying system, which satisfies the following system transition:

$$x(t+1) = A(t)x(t) + B(t)u(t) + w(t), t = 0, \ldots, T-1 \tag{B-1}$$

Equation (B-1) can be rewritten as:

$$x = Gw + Hu + x_0 \tag{B-2}$$

where

$$G = \begin{bmatrix} 0 & & & & \\ A_1^1 & 0 & & & \\ A_1^2 & A_2^2 & 0 & & \\ & & & \ddots & \\ & & & & 0 \\ A_1^T & A_2^T & \ldots & \ldots & A_T^T \end{bmatrix},$$

$$H = \begin{bmatrix} 0 & & & & \\ A_1^1 B(0) & 0 & & & \\ A_1^2 B(0) & A_2^2 B(1) & 0 & & \\ & & & \ddots & \\ & & & & 0 \\ A_1^T B(0) & A_2^T B(1) & \ldots & \ldots & A_T^T B(T-1) \end{bmatrix},$$

and $$x_0 = (x(0), A_0^1 x(0), \ldots, A_0^T x(0)^T$$

where $A_\tau^t = A(t-1)A(t-2)\cdots A(\tau)$, and $A_t^t = I$

Then we consider a causal feedback affine controller, which have the form of:

$$u(t) = \varphi_t(x(0), \ldots, x(t)) = u_0(t) + \sum_{\tau=0}^{t} F(t,\tau)x(\tau) \tag{B-3}$$

φ_t is called the control policy. With a close-loop system, the feedback matrix can be defined as:

$$F = \begin{bmatrix} F(0,0) & .. & \\ F(1,0) & F(1,1) & \\ & & \\ F(T-1,0) & F(T-1,1) & F(T-1,T-1) \end{bmatrix}$$

Then we will have

$$u = Fx + u_0 \tag{B-4}$$

With (B-2) and (B-4), we can solve for x and u in terms of w, to get

$$\begin{bmatrix} x \\ u \end{bmatrix} = Pw + \begin{bmatrix} \tilde{x} \\ \tilde{u} \end{bmatrix} \tag{B-5}$$

Where P is called close-loop matrix

$$P = \begin{bmatrix} P_{xw} \\ P_{uw} \end{bmatrix} \tag{B-6}$$

$$P_{xw} = G + HF(I - HF)^{-1}G$$

$$P_{uw} = F(1 - HF)^{-1}G$$

And

$$\tilde{x} = x_0 + Hu_0 + HF(I - HF)^{-1}(x_0 + Hu_0)$$

$$\tilde{u} = F(I - HF)^{-1}(x_0 + Hu_0) + u_0$$

The optimization problem is in general not convex in the design variables F and u_0. By a suitable *Q*-design procedure, however, these problems can be cast as convex optimization problems, and therefore solved efficiently:

Define

$$Q = F(I - HF)^{-1} \tag{B-7}$$

Then

$$F = (I + QH)^{-1}$$

Define

$$r = (I + QH)u_0 \tag{B-8}$$

Then

$$u = (I + FH)r$$

Then the close-loop matrix P becomes

$$P = \begin{bmatrix} P_{xw} \\ P_{uw} \end{bmatrix} = \begin{bmatrix} (I + HQ)G \\ QG \end{bmatrix} \tag{B-9}$$

$$\tilde{x} = (I + HQ)x_0 + Hr$$

$$\tilde{u} = Qx_0 + r$$

Therefore:

$$x = (I + HQ)GW + (I + HQ)x_0 + Hr \tag{B-10}$$

$$u = Q(GW + x_0) + r \tag{B-11}$$

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