Hybrid wind-diesel power plant valuation and optimization using real option theory and dynamic programming

by

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Abstract

Hybrid wind-diesel power systems have a great potential in providing energy supply to remote communities. Compared with the traditional diesel systems, hybrid power plants are providing many advantages such as providing extra energy capacity to the micro-grid, reducing pollution and greenhouse-gas emissions, and hedging the risk of unexpected fuel price increases.

This dissertation aims at providing novel insights for assessing and optimizing hybrid wind-diesel power systems considering the related uncertainties. Since wind power can neither be controlled nor accurately predicted, the energy harvested from a wind turbine may be considered a stochastic variable. This uncertain nature of wind energy source results in serious problems for both the operation and value assessment of the hybrid wind-diesel power system. On the one hand, regulating the uncertain power injected from wind turbines is a difficult task when operating the hybrid system. On the other hand, the economic profit of a hybrid wind-diesel system is achieved directly through the energy delivered to the power grid from the wind energy. Therefore, the uncertainty of wind resources has increased the difficulty in estimating the total benefits in the planning stage.

The main concern of the traditional deterministic model is that it does not consider the future uncertainty when making the dispatch decision. Thus, it does not provide flexible operational actions in response to the uncertain future scenarios. Performance analysis and computer simulation on the San Cristobal Wind Project demonstrate that the wind power
uncertainty, control strategies, energy storage, and the wind turbine power curve have a significant impact on the performance of the system.

In this dissertation, the relationship between option pricing theory and decision making process is discussed. A real option model is developed and presented through practical examples for assessing the value of hybrid wind-diesel power systems. Results show that operational options can provide additional value to the hybrid power system when this operational flexibility is correctly utilized. This framework can be applied in optimizing short term dispatch decisions considering the path-dependent nature of the optimal dispatch policy, given the plausible future realizations of the wind power production.

Comparing with the existing valuation and optimization methods, result from numerical example shows that the dispatch policy resulting from the proposed optimization model exhibits a remarkable performance in minimizing the total fuel consumption of the wind–diesel system. In order to make optimal decisions, power plant operators and managers should not just focus on the direct outcome of each operational action; neither should they make deterministic decisions. The correct way is to dynamically manage the power system by taking into consideration the conditional future value in each option in response to the uncertainty.
El sistema de energía eólica-diesel híbrido tiene un gran potencial en la prestación de suministro de energía a comunidades remotas. En comparación con los sistemas tradicionales de diesel, las plantas de energía híbridas ofrecen grandes ventajas tales como el suministro de capacidad de energía extra para "microgrids", reducción de los contaminantes y emisiones de gases de efecto invernadero, y la cobertura del riesgo de aumento inesperado del precio del combustible.

El principal objetivo de la presente tesis es proporcionar nuevos conocimientos para la evaluación y optimización de los sistemas de energía híbrido eólico-diesel considerando las incertidumbres. Dado que la energía eólica es una variable estocástica, ésta no puede ser controlada ni predecirse con exactitud. La naturaleza incierta del viento como fuente de energía produce serios problemas tanto para la operación como para la evaluación del valor del sistema de energía eólica-diesel híbrido. Por un lado, la regulación de la potencia inyectada desde las turbinas de viento es una difícil tarea cuando opera el sistema híbrido. Por otro lado, el beneficio económico de un sistema eólico-diesel híbrido se logra directamente a través de la energía entregada a la red de alimentación de la energía eólica. Consecuentemente, la incertidumbre de los recursos eólicos incrementa la dificultad de estimar los beneficios globales en la etapa de planificación.

La principal preocupación del modelo tradicional determinista es no tener en cuenta la incertidumbre futura a la hora de tomar la decisión de operación. Con lo cual, no
se prevé las acciones operativas flexibles en respuesta a los escenarios futuros. El análisis del rendimiento y simulación por ordenador en el Proyecto Eólico San Cristóbal demuestra que la incertidumbre sobre la energía eólica, las estrategias de control, almacenamiento de energía, y la curva de potencia de aerogeneradores tienen un impacto significativo sobre el rendimiento del sistema.

En la presente tesis, se analiza la relación entre la teoría de valoración de opciones y el proceso de toma de decisiones. La opción real se desarrolla con un modelo y se presenta a través de ejemplos prácticos para evaluar el valor de los sistemas de energía eólica-diesel híbridos. Los resultados muestran que las opciones operacionales pueden aportar un valor adicional para el sistema de energía híbrida, cuando esta flexibilidad operativa se utiliza correctamente. Este marco se puede aplicar en la optimización de la operación a corto plazo teniendo en cuenta la naturaleza dependiente de la trayectoria de la política óptima de despacho, dadas las plausibles futuras realizaciones de la producción de energía eólica.

En comparación con los métodos de valoración y optimización existentes, el resultado del caso de estudio numérico muestra que la política de operación resultante del modelo de optimización propuesto presenta una notable actuación en la reducción del consumo total de combustible del sistema eólico-diesel. Con el fin de tomar decisiones óptimas, los operadores de plantas de energía y los gestores de éstas no deben centrarse sólo en el resultado directo de cada acción operativa, tampoco deberían tomar decisiones deterministas. La forma correcta es gestionar dinámicamente el sistema de energía teniendo en cuenta el valor futuro condicionado en cada opción frente a la incertidumbre.
To my family, my parents, my grandparents,

To the people that I love and love me.
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Chapter 1

Introduction

This dissertation aims at providing novel insights for assessing and optimizing hybrid wind-diesel power systems considering the related uncertainties. The first chapter starts by describing the background of the work presented. The challenge and research questions are raised and discussed. Then, the research objectives and contributions are presented. Finally, the chapter layout of the dissertation is listed.

1.1 Background: Hybrid wind-diesel applications

One of the major applications of hybrid wind-diesel power systems is to provide energy supply for remote areas which are far from the mainland grid, such as islands and isolated villages (Senjyu et al., 2005). The high cost is the most obvious barrier to extending the existing power grid to remote communities. Due to the great distances, the lack of means of transportation, difficult terrain and poor infrastructure, the extension of grid cables requires a huge capital investment. It is not practical in economic terms to build
long transmission systems and ancillary facilities to serve a small remote village with low population (Anyi et al., 2010).

Traditionally, diesel energy is the main power source used in remote communities and facilities due to its reliability, trustworthy technology, and relatively low cost compared to other alternatives. According to (Katiraei and Abbey, 2007), remote communities in Canada have been supplied with electricity almost exclusively by diesel units. However, apart from the fuel consumption, a disadvantage of diesel based solutions is the the cost related to loss of diesel fuel in transportation and the cost of operation and maintenance (O&M) of the system. In addition, there is increasing concern over the environmental impact of diesel systems Integrating renewable energy capacity with traditional diesel power systems has been extensively researched in recent years. Among the various renewable energy sources, wind power is considered a competitive alternative to fossil fuels. A number of demonstration and commercial projects with integrated wind power have been established around the world. Wind turbines are constructed and connected to the local micro-grid, working together with the existing diesel power generators (Akikur et al., 2013) (Drouilhet and Shirazi, 2002b). Nowadays, it has become a widely accepted solution for providing power supply in remote and isolated communities.

Simply put, wind energy is generated by converting the kinetic energy of wind into electrical power. The kinetic energy first pushes and rotates the blades of wind turbines when passing through them, and finally provides energy to rotate the electric motor through mechanical connections. Thus, wind energy is a clean energy source since there are no greenhouse-gas emissions or other associated forms of pollution when producing electricity.
The purpose of integrating wind energy into isolated micro-grids is not just limited to providing clean energy and to replacing diesel fuel consumption in power generation. In addition, the hybrid energy system may offer significant advantages over traditional diesel power systems by increasing the total capacity, reducing pollution and green-house-gas emission and saving the cost of fuel consumption and transportation.

1.2 The Challenge in valuating and operating the hybrid wind-diesel power systems

Wind uncertainty is a clear challenge for hybrid wind-diesel systems. Depending on the design, the output of a wind turbine within a certain time period is determined by the wind characteristics of its location. Any change in wind speed and direction will significantly affect the working status and the output power of the wind turbine.

Since wind power can neither be controlled nor accurately predicted, the energy harvested from a wind turbine may be considered a stochastic variable related to the stochastic wind speed and direction. This uncertain nature of wind energy source results in serious problems for both the operation and value assessment of the hybrid wind-diesel power system.

On the one hand, regulating the uncertain power injected from wind turbines is a difficult task when operating the hybrid system. The power flow supplied to the micro grid should be controlled in phase with the real time power load, in order to maintain a constant power voltage and frequency (Sebastián and Quesada, 2006). In other words, the power flow dispatch scheme should ensure a balance between the power generation and
power demand. Since wind power is not totally predictable, it requires more reaction range and less reaction time for the control system to balance the unpredictable power change than in a static situation (Lin et al., 2010). Additional power reserve and spinning power are, thus, necessary for increasing wind energy penetration (Liu and Tomsovic, 2012). The additional spinning power reserve would decrease the total system efficiency since the diesel capacity is running in a low-efficiency region. As a result, system operators are facing a conflict of interest in increasing the system efficiency while maintaining the system security and reliability.

On the other hand, the economic profit of a hybrid wind-diesel system, together with other social-economic and environmental benefits, are achieved directly through the energy delivered to the power grid from the wind energy. Therefore, the uncertainty of wind resources has increased the difficulty in estimating the total benefits in the planning stage. Considering the high initial investment and construction cost of wind turbines, accurate and detailed analysis regarding to the feasibility of the project are of great importance. To obtain a detailed profit simulation, project managers have to simulate not only the uncertain character of wind power, but also the detailed operational strategy and the corresponding system response.

In summary, a successful integration of the wind energy source into remote isolated power grids or a comprehensive feasibility study that correctly estimates the total benefit and cost should be based on an advanced simulation model of uncertain parameters and an optimal dispatch model that utilize different energy sources in an efficient way while maximizing the profit.
1.3 Research question

Traditionally the power dispatch of hybrid wind-diesel systems is achieved based on deterministic tools. In general, the simulated wind power series and the power load series are used by a predefined deterministic minimization process which tries to utilize the cheapest energy source under certain restrictions (Lilienthal et al., 2005). Then, the profit estimation is tackled using the Discounting Cash Flow (DCF) method (Desideri and Yan, 2012) (Rehman et al., 2012) (Anwari et al., 2012). The cost for a certain time period is firstly calculated and then discounted as if the costs were met at the present time, (present cost). The total net present cost is considered to be the sum of all the present costs in the project life, a detailed dispatch process with deterministic approach will be discussed in Chapter 2.

The main concern of the traditional model is that it does not consider the future uncertainty when making the dispatch decision. If the future uncertainty has an impact, the optimal working status for a hybrid power plant does not only depend on what happens now, but also on what happens in the future. However, the deterministic operational strategies do not provide flexible operational actions in response to the uncertain future scenarios. The discounted cash flow method would not be sufficient for a global optimization since it does not fully utilize the flexibility according to the future uncertainty.

In this dissertation, we focus on answering the following questions.

- Will the future uncertainty of wind resources or other uncertainties affect the cash flow of a hybrid wind-diesel power system?
- If so, how can decision makers make optimal system operators make optimal
decision according to the current situation, and adjust those decisions according to the different scenarios under uncertainty?

- How can those decisions be made in a quantitative manner?
- Can we improve the computation of the present time value of a hybrid system?
- Can we optimize the amount of wind MW to be installed at the outset?

### 1.4 Research Objectives and contributions

In order to answer the question if the future uncertainty may be managed using flexible operational actions when operating and valuating the hybrid wind-diesel power systems, the first objective of this dissertation is to present the impact of uncertainty of a hybrid wind-diesel power system and show the potential improvement if the uncertainty is correctly addressed and accommodated in the operational process.

In the next step, a quantitative decision model is necessary to optimize the decision process under uncertainty. In this dissertation we intend to create a general model, which can be used in valuating and operating the hybrid wind-diesel power generating plants. This model should include the correct response to the realization of uncertain scenarios while taking the advantage of operational flexibility. As a result, the following character should be covered by the quantitative model.

- Integration of a stochastic wind speed and demand model within the optimization algorithm.
- Quantitative analysis of the effect of uncertainty on wind speed and demand.
• Optimization of decisions and operational policy under uncertainty by maximizing the net cash flow of the plant.

We choose the real option theory as the theoretical foundation to quantify and optimize the decision making process and the corresponding cash flow generated by the power producing process at different time stages. The advantage of the real options model is that it offers a simple but effective integration method of the future uncertainty in a time-dependent decision making process. Thus, an uncertainty source such as the wind resource, as well as the stochastic demand, may be dynamically modeled. Besides, different mathematical methods are available in the literature to solve the real option problems.

Taking real option theory as the theoretical basis for optimizing the decision policy, this dissertation presents a quantitative model for evaluating the operational flexibility of the hybrid system, and thereby, to achieve the following objectives.

• To optimize the operational strategy and dispatching process to achieve maximized cash flow in the given time period, while taking into consideration the uncertain variables. By comparing the performance of the traditional operational strategy and the proposed one, we prove that the optimal operational decisions for an hybrid wind-diesel power system depend on the uncertain future and its current working status.

• To achieve an accurate valuation of the hybrid wind-diesel power plant through optimized short term dispatching considering the uncertainty related to the both the wind speed and the demand level.

• To determine the optimal system configuration based on the wind quality and the local demand character based on the valuation model.
To develop advanced applications dedicated to daily operation and management for the hybrid wind-diesel power systems, in order to improve the cash flow, increase the fuel efficiency, while maintaining the power supply with quality and safety.

To achieve the research objectives mentioned above, we firstly show that the wind resource uncertainty should be taken into consideration when valuating and operating the hybrid plant. As a conclusion of the practical case study on one of the largest hybrid wind-diesel power plants in the world (presented in Chapter 5), we show that novel dispatching strategy and control mode for diesel engines are necessary to improve the diesel efficiency.

Subsequently, operational strategies for hybrid power systems are studied. Based on the real option theory, a dynamic programming method is developed to generate the optimum operational policy while maximizing the net cash flow of the hybrid power plant.

We demonstrate that an optimal operation strategy under uncertainty can be applied in short term applications such as daily self scheduling, energy production commitment, and short term maintenance, also in long term valuation and project planning.

Comparing with the existing valuation methods, this research has introduced the following unpublished features in the application of operation and valuation of hybrid wind-diesel power systems:

- Optimization of the dispatching schedule: the switching option provides operational flexibility in response to the uncertain wind speed.
- Optimization of the system configuration: the project value depends on the scale of wind speed distribution. An optimal number of wind turbines may be devised at the outset due to the limitation of demand and local wind power abundance.
• Full valuation of the project accounting for the optimized cash flows, resulting from the optimal dispatching schedule.

• Practical application of optimal diesel dispatch: due to the nonlinearity of the diesel engine power curve, optimal diesel dispatch may be used to improve the diesel efficiency and increase the cash flow of the project.

1.5 Chapter layout

Chapter 1 presents an introduction to this dissertation. We describe the application of hybrid wind-diesel power systems while emphasizing the challenges caused by the uncertainty when operating and valuating the hybrid power plant. The research question is then raised. And to solve the problem, the research objectives and tasks are listed. Finally, we present the chapter outline.

Chapter 2 provides an overview of hybrid wind-diesel power systems. We introduce the main components, the penetration level, the related wind uncertainty, and the dispatch principles of the hybrid system.

Chapter 3 overviews the option pricing theory with a numerical example. We discuss the relationship between the decision making process and the corresponding uncertainty. We emphasize that proactive risk management may be achieved if the operational flexibility is correctly addressed and accommodated. Finally the real option theory is introduced through an extension of option pricing theory.

Chapter 4 summarizes the most used numerical methods in option pricing models. Then, we extend the discussion to general optimization and decision making methods,
including the stochastic programming and Markov decision process. We conclude that the conditional value should be calculated when making decisions in an uncertain environment.

The model presented in this thesis is incorporated in Chapters 5, 6, and 7, through practical examples in two different conceptual frameworks. These chapters are presented in the form of research papers.

Chapter 5 includes a case study on one of the largest hybrid wind-diesel power plants: The San Cristobal Wind Project (Global Sustainable Electricity Partnership (GSEP), 2013) is taken as an example to illustrate the main issues concerned with operating and managing hybrid power systems.

Chapter 6 presents a study for valuating the wind energy uncertainty with switching options. We show that additional value may be achieved by a correct response to wind uncertainty, while the optimal scale of wind power depends on the character of the demand and the local wind resource.

Chapter 7 develops a practical method to optimally determine the diesel dispatch scheme for an isolated hybrid power grid. Compared to the traditional deterministic dispatch scheme, we show that high diesel efficiency may be achieved using the strategy generated by the proposed method.

Chapter 8 concludes this dissertation and provides some suggestions for future research.
Chapter 2

Hybrid wind-diesel generation systems

This dissertation focuses on hybrid wind-diesel power systems, which combine diesel power generators with wind turbines as an alternative energy source. Table 2.1 and Figure 2.1 show an example of a hybrid wind-diesel power supply system installed in Alaska, USA (Drouilhet and Shirazi, 2002a). The power plant provides power to a village and supplies the electrical load and several thermal loads. The operating and maintenance algorithms try to minimize the working hours of the diesel power generators and the consumption of diesel fuel. Wind turbines are connected directly to the power distribution grid of the village through transformers, and the diesel generators are of the synchronous type. The system also includes dump load components and controllers for the heating elements.

In this chapter, we present a brief introduction to hybrid wind-diesel power systems. We introduce some basic concepts, such as the system components, wind penetration
<table>
<thead>
<tr>
<th>Qty</th>
<th>Component</th>
<th>Rating</th>
<th>Make and Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>Wind Turbine</td>
<td>65kW</td>
<td>Atlantic Orient Corp. 15/50</td>
</tr>
<tr>
<td>1</td>
<td>Diesel Generator</td>
<td>168kW</td>
<td>Cummins LTA10</td>
</tr>
<tr>
<td>1</td>
<td>Diesel Generator</td>
<td>75kW</td>
<td>Allis Chalmers 3500</td>
</tr>
<tr>
<td>1</td>
<td>Diesel Generator</td>
<td>168kW</td>
<td>Cummins LTA10</td>
</tr>
<tr>
<td>1</td>
<td>Local Dump Load Controller</td>
<td>89kW</td>
<td>NERL Design</td>
</tr>
<tr>
<td>1</td>
<td>Remote Dump Load Controller</td>
<td>144kW</td>
<td>NERL Design</td>
</tr>
<tr>
<td>1</td>
<td>Rotary Converter</td>
<td>159kVA</td>
<td>NERL Design</td>
</tr>
<tr>
<td>200</td>
<td>Battery Cell</td>
<td>1.2VDC 130Ah</td>
<td>SAFT SPH130</td>
</tr>
<tr>
<td>1</td>
<td>Auxiliary Battery Charger</td>
<td>300VDC 30A</td>
<td>NERL Design</td>
</tr>
</tbody>
</table>

Table 2.1: Typical components of wind diesel hybrid energy system.

level, dispatching criteria, and the deterministic dispatching approach.

2.1 System components

2.1.1 Diesel generator

Diesel generators are widely used for supplying electricity power in remote communities without connection to the power grid. The reason of using diesel generators includes the long life-time and durability, relative cheaper cost per wattage compared to other generators, and cheaper cost of diesel fuel compared to other fuels (Whitaker, 1996).

The disadvantages include pollution, noise, and smoke emitted when running the generator, the high maintenance cost, and the relatively long time for the generator to ignite when started (Wenham, 2011).

The diesel generator is a combination of a diesel engine and an electric motor. The kinetic energy generated from the diesel engine is converted into electrical energy. The capacity of a diesel generator may be ranged from several kW up to two thousand kW.
Figure 2.1: Typical wind diesel hybrid energy system example.

With the help of a control system, a security circuit, a starting system, and other related control and safety devices, several diesel generators can be connected together to form a synchronized power plant (Katiraei and Abbey, 2007).

Several issues should be considered for operating and maintaining the diesel generators. The fuel consumption rate is defined as the amount of diesel fuel that is used to produce a specific amount of electrical power. According to (Skarstein and Uhlen, 1989), the diesel power efficiency for a certain diesel generator is, in general, higher if the diesel generator is working near to its rated capacity.
Figure 2.2 shows a typical fuel consumption curve of a diesel generator (Nayar, 2010). When the output power is $22.5\text{kW}$, the diesel consumption is $9L/h$, and the diesel power efficiency can be calculated as $2.5\text{kW}/L$. Likewise the diesel efficiency is $2.8\text{kW}/L$, and $3.2\text{kW}/L$, and for the output power $33.8\text{kW}$ and $45\text{kW}$ respectively. Due to the incomplete combustion of fuel during a low power load, a diesel generator consumes more fuel per unit of energy when the output power does not reach the rated capacity.

Figure 2.2: Typical fuel consumption curve of diesel generator with 50kVA rated capacity.

For an isolated power grid, since the electrical power production should be balanced according to the energy demand, the diesel generators are often working in a low capacity range due to the limitation of low energy load. Diesel power generators also suffer damages when the diesel engine is running at low speed or with low electricity load (Bachi, 2012), especially when the engine is idling as a backup power generator. Some restrictions on the minimum power load are normally applied to protect the diesel generators.
Ideally, diesel engines should not run below 30% of their rated load. Short periods of running the generator at light loads are allowed if the generator is brought up to full load, or close to full load, on a regular basis. If the system uses one generator as the main power source, the generator will operate at light load in some period of time which will reduce the total efficiency and life time cycle and increase the maintenance cost (Bachi, 2012).

(Nayar, 2010) argues that employing a dual diesel generator system results in some fuel savings, but managing this dual system is time consuming and impractical. The basic idea for the dual diesel system is that when the load is light, the smaller generator is used; as the load increases, the manual switch transfers to the larger generator.

2.1.2 Wind turbines

A wind turbine is a device that harnesses the energy from wind and converts the mechanical energy into electricity. The basic components of a wind turbine include blades, shafts, gears, electricity generator and the connecting cables. When the wind comes through the blades and turns the rotors, the kinetic energy in the wind is converted into mechanical energy through the rotational shaft. Power generator is finally driven by mechanical power to generate electricity. Depending on the axis of rotation, the wind turbines may be divided into two general groups: the horizontal-axis wind turbines and the vertical-axis wind turbines. The horizontal-axis wind turbines are more commonly used than the horizontal-axis ones.

Since wind power is generated from the kinetic energy of air, the total wind power
through an area $A$ may be calculated in with the following equation:

$$P_w = \frac{1}{2} \times A \times \rho \times V_w^3,$$

(2.1)

where $\rho$ is the air density, and $V_w$ is the wind speed.

According to Equation 2.1, the power capacity of a horizontal-axis wind turbine under a given wind condition depends on the area that its wind blades may cover. A wind turbine with longer blades means a larger $A$ in the wind power formula and therefore more energy would be harvested. Figure 2.3 shows the historical growth of the wind turbine diameter and the rated capacity from 1980 to 2010 (Sointu, 2014).

Another factor that should be considered is the wind speed. The wind power is proportional to the cube of the wind speed $V_w$. Therefore, wind speed has a significant impact on the wind power. If the wind speed doubles, the theoretical wind power increases eightfold accordingly.

Due to different designs, the power performance curve is different for each wind
turbine. Figure 2.4 shows an example of a hypothetical wind turbine power curve, which represents the energy production under various hub-height wind speed conditions. Source from (Manwell et al., 2010). The cut-in wind speed represents the minimum wind speed at which the wind turbine delivers useful power. The rated wind speed is the wind speed at which the rated power output is reached, and the rated power is in general the maximum power output of the electrical generator. The cut-out wind speed is the maximum wind speed at which the wind turbine is allowed to deliver power, in order to prevent damage to the system under too high wind speed (Manwell et al., 2010).

![Example hypothetical wind turbine power curve](image)

Figure 2.4: Example hypothetical wind turbine power curve.

According to (Hunter and Elliot, 1994), when selecting a wind turbine, the relative size of the wind turbine would be a primary concern. The larger the rotor size, the more energy a wind turbine could deliver to the system. However, a larger wind turbine will imply more system complexity due to the wind uncertainty. They also suggest that the
wind, load environmental, and other factors should be assessed before the selection of wind turbines.

2.1.3 Energy storage systems

Energy storage capacity is also a central element in isolated power grids (García and Weisser, 2006). Indeed, despite the fact that electrical power cannot be stored on a large scale, research work has shown that storage technologies could be very helpful for isolated grid systems by providing small scale-energy storage (Ibrahim et al., 2008). In the high-wind period, apart from providing the required energy load, the excess wind power can be stored in the energy storage system in another form. And in the low-wind period, the stored energy can be re-converted into electrical power to provide energy. At the same time, the energy storage system provides additional power stability and security to the system by smoothing the frequency and voltage change and providing reserve power.

Different technologies, including but not limited to electrochemical batteries, hydrogen storage, flywheel systems, and pumped hydraulic energy storage, can provide short-term energy supply from a few seconds to a few hours, with a power output ranging from a few kW up to about one GW, and the total energy stored could range from less than 1 kWh to tens of GWh. Figure 2.5 shows a summary of the power output and the capacity for different energy storage systems (Ibrahim et al., 2008).

2.1.4 Control system and other components.

Apart from the main elements such as the diesel generators, wind turbines, and energy storage, other components are necessary for the operation and maintenance of the
hybrid wind-diesel power system. For example, a dump load is used to consume the excess power in the high-wind period, or when an unpredictable increase in wind power output occurs, and a supervisory and control system is required to decide the dispatch strategy, maintain the system balance and keep a stable power frequency and voltage. Depending on the system configuration, Clark claims that more sophisticated components and control systems will be required with the increase of the penetration level (Clark, 2013).

In the case of the wind system installed in Alaska (Drouilhet and Shirazi, 2002b), several operating modes of wind diesel hybrid plants exist, depending on the power demand and wind power availability. When the wind energy cannot cover the electricity demand, the diesel power generator will run continuously, and wind energy will run only when available,
and the diesel power plant will also respond in order to control the power frequency and voltage. If the wind power is sufficient, the diesel power generator is only started when the wind power generator does not meet the load with adequate margins. In this case, the power frequency and voltage is controlled by an AC machine connected to a storage battery. In order to reduce the fuel consumption of the system, the component dispatching process is extremely important. This process determines whether each of the individual components should be started, to meet the capacity demand. Statistical dispatching is often applied by turning the component on or off in order to meet the energy imbalance of energy based on the prediction of weather and demand in the near future, and instantaneous dispatching prevents sudden and unpredictable changes in load and power generation.

2.2 Penetration level of the wind diesel generation plant

Depending on the penetration level, the wind-diesel power systems may be classified as low-penetration systems, mid-penetration systems, or high-penetration systems. (Baring-Gould et al., 2003) A higher penetration-level system can save a maximum level of fuel when the diesel power generators are turned off during high wind availability. And at the same time, the complexity involved in the control system increases with higher penetration.

According to (Baring-Gould et al., 2003), in the low penetration plants, “wind acts as a negative load, very little control or integration of wind turbines into the power system is needed”. Diesel power generators will provide energy supply in maintaining all “frequency, voltage and reactive power requirements”. It could be considered as an integration of wind
power in the existing system with small modifications, a level of up to 20% of fuel saving may be expected from adding wind turbines.

When the penetration increases to a medium level, wind energy plays a more important role in the system but still acts as a negative load. Meanwhile there is still a strong need of diesel power to provide the rest of the energy gap and ensure the energy quality and stability. In this system, the diesel power generators are expected to be working at all times. More additional components should be introduced, including system frequency control, release excess power and VAR support, (Baring-Gould et al., 2007); it also requires diesel power generators to cover a wide range of the operating region.

In the high penetration level, diesel power generators could be shut off when the wind power is high enough, and “complete integrated power system with advanced control” is needed. For example, “system frequency is maintained by dispatching loads and controlled dump, system voltage and reactive power are controlled by synchronous condensers, and active control devices is applied to reduce the variability” (Baring-Gould et al., 2003). In some systems, storage system is also applied for filling short gaps. Automated operation control and fail safe operation strategy is highly required in the high penetration system. Table 2.2 provides a summary of the characteristics of different system penetration levels for hybrid wind-diesel power systems. Source from (Baring-Gould et al., 2003).

According to the recent report by the Alaska Energy Authority and Denali Commission (Fay et al., 2010), Medium and High penetration systems are costly, compared with low penetration systems, and more complex to operate, but wind energy generates a
### Table 2.2: Summary of penetration level for hybrid wind-diesel power systems.

<table>
<thead>
<tr>
<th>Penetration Class</th>
<th>Operating Characteristics</th>
<th>Penetration Peak</th>
<th>Penetration Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>Diesel run full-time&lt;br&gt;Wind power reduces net load on diesel&lt;br&gt;All wind energy goes to primary load&lt;br&gt;No supervisory control systems</td>
<td>&lt;50%</td>
<td>&lt;20%</td>
</tr>
<tr>
<td>Medium</td>
<td>Diesel run full-time&lt;br&gt;Secondary load is dispatched by excess wind power&lt;br&gt;Requires simple control system</td>
<td>50%-100%</td>
<td>20%-50%</td>
</tr>
<tr>
<td>High</td>
<td>Diesel may be shut down during high wind availability&lt;br&gt; Auxiliary components required to regulate the system&lt;br&gt;Requires sophisticated control system</td>
<td>100%-400%</td>
<td>50%-150%</td>
</tr>
</tbody>
</table>
large percentage of electric demand. It also potentially provides energy for space heating or other uses—like electric cars. The High penetration systems offer large potential for future development, including the ability to store excess electricity in a battery system, offset residential and commercial space heating, enhance alternative transportation such as electric vehicles, and applying Smart Grid load management systems to achieve the full integration of wind power, diesel generation, and the electric load. The report showed that the Annual fuel savings could potentially be increased by 10% through employing Smart Grid solutions, when this technology becomes economically viable.

2.3 System dispatching criteria

Specifically for the isolated hybrid grid, the uncertainty of wind energy has a significant impact on the system security and reliability. Especially for the systems with a high wind penetration, any change in wind turbine output will result in a significant power fluctuation when compared with the total scale of the grid.

Consequently, automatic and dynamic power balancing is necessary in the daily operation of a hybrid wind-diesel system to absorb the unpredictable power fluctuation caused by wind changes and to maintain the system security and reliability. The dispatch process decides whether to turn on/ off each component in the system such as the diesel power generators, wind turbines, load dumps, batteries, and the decision depends not only on the electricity demand but also on the capacity of both the diesel and wind turbines.

In order to maintain the quality of electricity power supply, the voltage and frequency in the isolated grid should be constant. Any imbalance of power or reactive power
will result in changes in the system voltage and frequency. The difference of real power imbalance will be stored as kinetic energy, which results in the change of rotating speed of the rotating machines in the system. This change in rotational speed of the synchronous machines will alter the electrical frequency, as shown in the following equation:

\[
\sum P_{\text{sources}} - \sum P_{\text{sinks}} = \frac{d(KE)}{dt} = \frac{d}{dt} \sum_{i=1}^{I_{\text{max}}} J_i \omega_i^2,
\]

where \(P_{\text{sources}}\) and \(P_{\text{sinks}}\) are the active power production and consumption, and \(KE\) is the kinetic energy of the system, \(J\) is the moment of inertia of rotating machine, and \(\omega\) is the angular velocity of rotating machine.

On the other side, the imbalance in reactive power will result in a change in voltage of the system. According to (Drouilhet and Shirazi, 2002b), unlike the case of real power, the reactive power cannot be stored in the system as kinetic energy, but is inherently balanced by the supply source and the sinks. The reactive power is a function of voltage, if the reactive power sources cannot supply the reactive power demand, the voltage will fall to a point such that the equilibrium is recovered, as shown in the following equation:

\[
\sum Q_{\text{sources}}(V_{AC}) - \sum Q_{\text{sinks}}(V_{AC}) = 0,
\]

where \(Q_{\text{sources}}\) and \(Q_{\text{sinks}}\) are the reactive power production and consumption, and \(V_{AC}\) is the AC bus voltage.

Different types of criteria are normally applied to power dispatching in a hybrid wind-diesel power system (Drouilhet and Shirazi, 2002b). The statistical dispatching criteria are based on the information in the near past to predict the wind power generation and
the electricity demand in the near future, and turn the components on or off in response to any unpredicted imbalances (Drouilhet and Shirazi, 2002b), and instantaneous dispatching is a backup to statistical dispatching, and it monitors instantaneous power values to insure immediate response for any sudden and unexpected system power imbalance. In order to save the diesel fuel and make the maximum profit, dispatching will also utilize the wind power as the first choice while keeping the quality of power supply.

For diesel power generators, the dispatching process decides the diesel capacity required which is the minimum amount of diesel capacity that should be online to ensure the primary load (Drouilhet and Shirazi, 2002b). And a certain reserve capacity should be maintained to prevent any sudden changes, such as the sudden drop of wind power or system failures. Meanwhile, the dispatching algorithm determines the wind turbine generating capacity and the working status of each of the wind turbines. Since the cost of energy generated from the wind power is significantly less than the power generated by the diesel power, an optimal combination of diesel generators and wind turbines should be determined to supply the required captivity.

2.4 Deterministic dispatch strategy

Dispatch strategy proposed by (Barley and Winn, 1996) has been widely applied in the area of hybrid power system operation and valuation. Some examples of the applications include the software HOMER (Hybrid Optimization of Multiple Energy Resources), HYBRID2, and other works (Dalton et al., 2008).

The term dispatch strategy, according to (Barley and Winn, 1996), refers to the
control policies that pertain to energy flows among the major components of the system. They argue that the key part of the controversy is whether to use the diesel power to charge the energy storage. The advantages of charging the battery with diesel include:

- The diesel fuel efficiency may be improved since the diesel engine is operating at the rated capacity.
- The frequency of switching on the diesel engine may be reduced.

In contrast the disadvantages include:

- The life time of the battery is reduced.
- Energy is lost during the storage and power conversion process.
- There are less opportunities to charge the battery using the cheaper renewable energy source.

The dispatch scheme (Barley and Winn, 1996) is based on several simple dispatch strategies. The fundamental decision of the strategies is to determine the amount of energy that is charged to / discharged from the energy storage. Then the system tries to use as much renewable energy source as possible. Diesel power is acting as back-up power source to balance the remaining power load.

The so-called Frugal discharge strategy is used to control the discharged power from the battery. If the net load is larger than a critical load, the diesel engine is used, because the diesel generation cost is less that the battery cost. In contrast, the diesel engine is stopped and the stored energy is used. This discharge strategy is used in conjunction with the other battery charging strategies.

Overall three battery charging strategies are proposed, namely the Load following
strategy, the SOC set point strategy and Full power/Minimum run time (FPMRT) strategy.

- In the Load following strategy, the energy storage is not charged at all with the diesel generated energy. The diesel engine is set to match instantaneously with the net load.

- In the SOC set point strategy, the battery is charged to a predefined SOC every time the diesel should be started, and the diesel power generator is operating at the highest capacity without dumping power.

- In the FPMRT strategy, the diesel engine is always running at the rated capacity for a prescribed minimum run time. This strategy is similar to the SOC set point strategy with a low set point.

It is argued that (Barley and Winn, 1996), by optimally choosing strategies from the Load following strategy and Full power strategy, the operational strategy may be virtually effective as the ideal one.

However, these dispatch strategies are deterministic, because the dispatch decision is determined only according to the current net load character and the state of charge for the battery. In other words, the decision in each time period would not be changed for different situations. Figure 2.6 shows this dispatch process with a decision flow chart (Barley and Winn, 1996). Note that decisions are made without considering the future uncertainty of wind power. Neither could the dispatch action be adjusted in different scenarios according to new information.

Compared with the ideal dispatch strategy, simple deterministic strategies provided by (Barley and Winn, 1996) are consuming more energy. The reason, as stated by
the same authors (Barley and Winn, 1996), includes

- With the load following strategy, the diesel genset is not running at its maximum efficiency.

- With the set point strategy, some of the diesel energy stored in the battery is wasted as spilled energy.

At the same time the cost of starting-up and shutting-down the diesel genset has been neglected.

Since perfect prediction is impossible for the uncertainties involved in the wind
power production, the power load and wind speed are not known in advance. Thus the real dispatch decision strategy should be a step-by-step process, where the uncertain information is revealed in the same manner.

In the next chapter, we present a discussion about decision theory under uncertainty. Different types of decision-making philosophy like the Here-and-Now decision and Wait-and-See decision are introduced and discussed using examples of financial options.
Chapter 3

Financial options and decision making under uncertainty

When operating the hybrid wind-diesel power plants, operational decisions make an impact on the performance and the cash flow at each time period. When the wind energy is sufficient, rather than burning the diesel fuel, it is more profitable to consume the energy produced by the wind turbines. In contrast, if the available wind energy is less than the expected demand, more expensive backup capacity is necessary to fill-in the gap preventing a blackout. Decisions on power scheduling have to consider both sides, to waste the excess wind energy or to prepare more inefficient spinning reserve. The uncertainty liked to the wind behavior makes the problem somehow sophisticated.

In this chapter, we present a brief introduction of the financial option and option pricing theory, which may be applied for quantitatively valuating a project and helping managers to make operational decisions. By discussing the relationship between the decision-
making process and the uncertainty, we focus on explaining how the future uncertainty can be adapted with the operational flexibility to change the risk distribution.

3.1 Introduction: Decision making in uncertain environments

We make many decisions in our daily life. For instance, when planning a city-break holiday, we have to decide which airline company to fly with, and then we may also need to decide if we should pay the ticket right away or keep waiting with the hope that there will be an special offer in the following days. When going to a lecture in the university, we have to decide from taking the bus just beside the entrance of our building or walking 10 minutes and taking the metro to avoid the traffic jam. We may also hesitate about whether to go for a picnic in a dark cloudy Sunday morning, while the weather report says we may expect a sunny day.

When we make these decisions, we are not in possession of complete information about what is going to happen next in the future. The lack of accurate predictions for future events implies uncertainty. Back to the examples mentioned above, when we book an airline ticket, we are not sure whether the company will start a new promotion or increase the price of the same route. When catching the bus, we do not know about the traffic situation on the road. And neither are we sure the weather will turn fine when we reach the park for the picnic even if the weather forecast says so.

Generally, we make decisions depending on our own risk tolerance. Sometimes we make aggressive decisions, for example, we may choose to take the bus because it is generally faster, but at the same time, we are taking the risk of being stuck in a traffic jam.
In contrast, we may be also conservative by cancelling the picnic plan and staying at home in a cloudy day.

So far, the decision-making process has not been adapted to uncertainty. In the examples mentioned above, a here-and-now decision should be made. We have to answer yes or no right away to the questions, whether to book the ticket, to take the bus, or to go for the picnic. Then, we accept all the consequences that our decision leads to, no matter whether the outcome is good or bad.

In real life, we make not only here-and-now decisions, but sometimes we also decide to be flexible and wait-and-see, and make modifications after we have more information. Now we can pay a premium to the airline company to lock the price of the ticket and pay it later. So we keep the option of buying a cheaper ticket in a couple of days and we are thus not shouldering form the risk of an increase in the price. Likewise, we could choose to drive in a route that is well connected to the metro stations or go to the picnic in a park next to a cinema. Even though it might be a little more or less interesting, we may easily park the car and switch to the metro when we foresee a high chance of traffic jam, or change the plan to the cinema when it starts raining.

Similarly to the daily-life decisions, most of the managerial decisions have to be made under uncertainty. Therefore, the proper decision-making process should be flexible to be adapted to the disclosure process of uncertain future. And in order to be able to quantitatively valuate the decision options and outcomes, a mathematical model is highly necessary to choose the optimal strategy taking into consideration the development of uncertain future events.
3.2 Discounted cash flow: valuation method for here-and-now decisions.

Quantitative methods are fundamental for managerial decisions. In many situations, managers need to calculate and compare different strategies, investments, and other kinds of operational actions in a quantitative manner. They need to understand why and how much decision A is better than another decision B. A simple and intuitive way is to calculate and compare the output, i.e. how likely the objective can be achieved.

When managerial decisions are made with the objective of value creation, discounted cash flow analysis (DCF) is a widely accepted method for firm or project valuation and planning (Rawley and Benton, 2009) (Simões and Farret, 2008) (Willis, 2000). One of the basic rules for this method reads “a dollar today is worth more than a dollar tomorrow,” (Brealey et al., 2006), because the dollar today can be invested to start earning interest immediately. In order to compare the cash flows with a single standard, the future cash flow should be discounted at a specific rate as if they occur at present - the Present Value (PV).

The present value, $PV$, can be calculated using the following equation:

$$ PV = \sum_{t=1}^{t=n} \frac{CF_t}{(1+R)^t}, \tag{3.1} $$

where

- $n$ is the life time of the asset
- $CF_t$ is the estimated cash flow in period $t$
- $R$ is the discount rate reflecting the risk of the estimated cash flows.
The uncertainty of the outcome of the decision is presented according to another basic rule in financial theory: “A safe dollar is worth more than a risky one” (Brealey *et al.*, 2006). The discount rate is the most important factor that represents the risk of the estimated cash flow. Specifically, the discount rate is higher for a riskier cash flow and lower for a safer return. For example, one feels (in fact, it really is) safer about your principal and interest, if you put your money into a bank rather than lending it to someone to open a restaurant.

To continue the example, given that the uncertainty of the returns from a commercial bank is low, the discount rate for calculating the present value of a saving in a bank is small, usually similar to a risk-free discount rate. A risk free discount rate is used to discount a certain cash flow, of which you are almost 100% sure about the return. The interest rate of sovereign bonds is a good example of benchmark of the risk-free discount rate.

When the risk grows, one will fell more uncertain about whether he or she will get the committed return in the future. A restaurant may be a success, but in the worst case, the investors would suffer a partial or full loss. As a result, in order to convince one into lending money to the restaurant rather than saving it in a bank, the restaurant should offer a much higher and more attractive future return than the bank interest.

The discounted cash flow method offers a rough method to connect decisions with uncertainty. As discussed previously, by discount future cash flow with a correct discount rate according to its uncertainty, a present value is calculated as the quantitative reference of the final valuation. However, when practically implemented, the discount cash flow method
shows its limitations in accurately assessing the value of flexible decisions.

The limitations are based on the fundamentals of the discounted cash flow val-
uations. When the future uncertain cash flow is discounted, the final goal is to obtain a
present value as a reference. In order to achieve this objective, decision makers need to
assume that they know not only the expected cash flow but also a correct discount rate.
As a result, the decision process is a here-and-now decision because the estimation of cash
flows and discount rates can only be based on present information. Managers cannot, for
example, delay the decision process since the uncertainty of the decision considered is going
to change with incoming information, and therefore change the discount rate.

Furthermore, when talking about flexibility, in many cases, the decision process
may be divided into different stages, where following actions can be made to enhance or
correct the previous decisions. The discounted cash flow is also inadequate for valuating
this kind of multi-stage decision process with the future cash flow depending on the forth-
coming uncertain events and the corresponding subsequent decisions. As concluded by
(Trigeorgis, 1996), the classical discounted cash flow method “doesn’t consider the value
of management’s flexibility to adapt and revise later decisions in response to unexpected
market developments”.

3.3 Decisions under uncertainty: financial options

So far, in the discounted cash flow method, since the discount rate depends on the
future uncertainty of the cash flow, the valuation should be calculated before the uncertainty
is revealed, and no feedback-decision is considered. In order to simulate the flexible decision
process in an uncertain environment, more appropriate models are necessary.

In financial markets, an option is one of the tools that offer the holder the right to react after the disclosure of uncertain events. The basic European option represents the right to buy or sell a predefined quantity of the underlying asset at a certain price at a specified date. Call and put options are two fundamental types of financial options.

In the case of a European call option, it offers the option holder the right to buy the underlying assets at a certain price (strike price) at the expiration date. Because the option offers a right but not an obligation, the option holder can choose at his own will (whether to exercise the option or not). Similarly, a European put option offers the right to sell the underlying asset at the expiration date at predefined strike price.

Comparing with the directly discounted cash flow method, the option model includes an additional decision process after the uncertain event is revealed, for example, if we decide to hold a stock, or a certain asset, for a specific time. During this time period, we passively accept the realization of the uncertain price changing of this asset. However, if we decide to hold a European option of the underlying asset, we need also to decide whether to exercise this option at expiration, knowing the exact price after the uncertain process.

For European call and put options, the additional decision making on the expiration date is obvious because of the simple payoff structure. For a call option, if the value of the asset is less than the strike price, the option shall not be exercised because it is cheaper to buy the asset directly in the market. As a result, the payoff is zero. On the other side, if the value of the asset is higher than the strike price, a rational option holder will choose to exercise the option and buy the asset at the strike price which is cheaper than buy the asset
directly in the market. The direct payoff of the option on the expiration date is, therefore, the difference between the asset price and the strike price of the option.

For a put option, the situation is similar. The option holder will only exercise the option to sell the underlying asset at the strike price when the actual price of the asset after the uncertain process is lower than the strike price. The payoff of the option will be also the difference between the strike price and the actual piece. Otherwise, the option will expire with zero-payoff. An example of the payoff diagrams and the corresponding decision structures for a European call and put option at expiration date is shown in Figure 3.1.

Figure 3.1: Example payoff function for European call and put options

Other than the simple European call and put options, the decision after the re-
alization of the uncertain process of the underlying asset can be more complex for other types of financial options. Table 3.1 shows some typical financial options with different payoff structure, and more payoff structure can be designed at the will of the option issuer. These payoff structures determine the decision strategy after the realization of the uncertain underlying asset.

<table>
<thead>
<tr>
<th>Option type</th>
<th>Character</th>
</tr>
</thead>
<tbody>
<tr>
<td>American option</td>
<td>Can be exercised on any trading time before expiration</td>
</tr>
<tr>
<td>Bermudan option</td>
<td>Can be only exercised on previously specified trading date</td>
</tr>
<tr>
<td>Asian option</td>
<td>The payoff is determined by the average underlying price over some pre-decided time period,</td>
</tr>
<tr>
<td>Barrier option</td>
<td>The payoff depends on whether the underlying price has triggered some specific threshold or “barrier” before it could be exercised</td>
</tr>
<tr>
<td>Binary option</td>
<td>The payoff depends on whether the underlying price has triggered some specific threshold or “barrier” before it could be exercised</td>
</tr>
<tr>
<td>Exotic option</td>
<td>Refer to options that include complex financial structure</td>
</tr>
</tbody>
</table>

Table 3.1: Typical financial options with different payoff structure.

The advantage of a financial option is that option holder may make the optimal decisions along the whole uncertain process (American options) or after the uncertainty is revealed (European options), but with trading conditions predefined in an uncertain environment. In other words, flexible decision is available because the option holder only exercises the option when it is profitable. At the same time, the option holder should pay a premium to the option issuer for profiting from the benefits mentioned above. In order to compute a fair value of the options, the valuation of financial option -option pricing model- is discussed in the next session.
3.4 Value of flexibility: Financial option pricing

The correct pricing model for a financial option is difficult to solve using the standard procedure because it is impossible to find an opportunity cost for capital. In other words, since “the risk of an option changes every time the stock price moves”, and “the expected rate of return investors demand from an option changes every time the stock price moves”, the discounting process is a dynamic process (Brealey et al., 2006).

The breakthrough was done by Black and Scholes. Other than the traditional valuation method, the basic idea of the Black and Scholes method is to create another asset, which is easier to valuate, replicating the option, and the option is considered to be a levered investment of the underlying asset. Particularly, they created a portfolio which is composed by the underlying asset and a risk-free asset, with this so created portfolio having the same payoff as the option. We will demonstrate this idea using the following numerical example.

Suppose there is a stock with the current price $S$ of 100$. The option we are going to valuate is a call option, with a strike price of 120$. The option is of European type, and the mature time is 2 time period. The risk free rate in this example is 10% per time periods. Our task is to calculate the correct price of the call option. For simplicity, we assume that the stock price changes either up or down in each time period. The detailed price realization process is shown in Figure 3.2. According to the payoff structure of the option, it will have a payoff of 80$ at the end of time period 2 only if the stock price gets 200$, in the other cases, the payoff of the option is 0.

In order to break the process into small problems, we first focus on the situation
after time period 1 when the stock price is 140$, the stock price can change to either 200$ (with a return of 80$ of the option), or 100$ (with a zero return of the option) when the option expires at time period 2.

For the situation considered, the current stock price is \( S \), we are now trying to construct a portfolio that will return the same cash flow as the call option. This portfolio is combined with a risk free asset with \( B \) dollars and an underlying asset with \( \Delta \) shares. The cash flow of the constructed asset should be the same as the payoff of the call option, as given by the following equations.

\[
Su \times \Delta + (1 + R_F)B = Cu, \tag{3.2}
\]

\[
Sd \times \Delta + (1 + R_F)B = Cd, \tag{3.3}
\]

where \( Su \), and \( Sd \) are the future stock prices if they move up or down respectively, \( Cu \) and
$Cd$ are the payoffs of the call option if the stock prices are $Su$, and $Sd$ respectively, and $R_F$ is the risk free discounting rate.

It is easy to solve the equations and obtain the value of $\Delta$ and $B$ as follows,

$$\Delta = \frac{Cu - Cd}{Su - Sd}, \quad \text{(3.4)}$$

$$B = \frac{Su \times Cd - Sd \times Cu}{(1 + R_F) \times (Su - Sd)}. \quad \text{(3.5)}$$

After solving the problem, it is found that if we buy 0.8 shares of the underlying stock and borrow 73$ from the bank, we will have exactly the same return as the call option in time period 2, because if the stock price goes up, 0.8 shares of stock would be 160$ and also we need to return 80$ to the bank (because of 73$ initial loan with the 10% risk free interest rate), and the final payoff of the created asset is 160$ – 80$ = 80$. In the other case, if the stock price falls to 100$, the 0.8 shares of stock would be 80$, and the loan worth -80$, thus the total return of this asset is zero, shown in the following table. Since the payoff of the option is replicated by the asset, the money we pay for the option in time period 1 should be the same as what we pay for the created portfolio, which is 0.8 shares of the asset plus 73$ of bank loan. Finally, the value of the call option in time period 1 with stock price of 140$ can be calculated as $(140$ \times 0.8$) – 73$ = 39$. Table 3.2 compares the final payoff for the replicating asset and the call option in both cases when the stock price goes up or falls.

The value of the call option for 70$ current price can be calculated using the same method. The replicated portfolio contains 0 shares of stock and 0$ of risk free asset,
Table 3.2: Payoff of the replicating asset and the call option

therefore, the option value for a 70$-stock on time period 2 is worthless. Since the two possible value of the 70$-stock are 100$ (if the stock price goes up) or 50$ (if the stock price goes down) at time period 2, neither 100$ nor 50$ is higher than the strike price of 120$, the option is clearly worth nothing in time period 1 if the price is 70$.

Applying the replicating principle, the value of the option in the first time period can be therefore solved with the same method, for both of the cases with stock prices equal to 140$ and 70$ as shown in Figure 3.3.

When the stock price is 140$ at time period 1, the value of the option is 39$ since we could pay 39$ to create an asset that replicates exactly the payoff of the option. And if the stock price is 70$, the value of the option is zero, because the option will never be exercised.

Having this in mind, the option value at the initial time is solvable since we know the fair value of the option in the second period. If the stock price is 140$ in time period 1, the payoff of the option at time period 1 would be 39$. In other words, this option can be sold at a fair price of 39$ in time period 1. In the other case, if the stock price is 70$ at time period 1, the option is worthless. The value of the option is 0 at time period 1 since nobody in the market will be interested in buying it with real money. Another portfolio is
Figure 3.3: Value of the call option at time period 1

created in time period 1 to replicate the payoff (value) of the option from the initial time
to time period 1, as shown in Figure 3.4.

Finally, the option value is solved as 20$ at the initial time, which equals to 0.56
shares of the stock at 100$ per share, plus a risk free bank loan of 36$.

3.5 Option pricing and probabilities in a risk neutral world.

The option pricing model does not consider the future forecast of the underlying
asset, because investing in an option is nothing more than a portfolio with the underlying
stock and a risk free asset. Specifically, an option is a predefined operational strategy of a
portfolio according to the uncertainty realization, even if the value of the option does not
depend on the forecast of the underlying asset. It can be numerically solved by an artificial probability distribution of the future uncertainty value.

From the option pricing theory, we know that the value of the option, \( C_{\text{option}} \), equals the value of the underlying asset and risk free asset in the replicating portfolio, as shown in the following equation:

\[
C_{\text{option}} = \Delta S + B, \tag{3.6}
\]

where

\[
\Delta = \frac{Cu - Cd}{Su - Sd}. \tag{3.7}
\]
\[ B = \frac{Su \times Cd - Sd \times Cu}{(1 + RF) \times (Su - Sd)}. \]  

(3.8)

If we define:

\[ Su = (1 + u)S, \text{ and} \]  

(3.9)

\[ Sd = (1 + d)S, \]  

(3.10)

the value of the option is equal to

\[ C_{\text{option}} = \Delta S + B = \frac{(u - RF)Cd + (RF - d)Cu}{(1 + RF) \times (u - d)}. \]  

(3.11)

If we define another variable \( \text{prob} \), which equals to

\[ \text{prob} = \frac{RF - d}{u - d}, \]  

(3.12)

pointed that \( d \leq RF \leq u \), \( \text{prob} \) is a number between 0 and 1, that is, a probability.

The value of the option can be written as

\[ C_{\text{option}} = \Delta S + B = \frac{\text{prob} \times Cu + (1 - \text{prob})Cd}{(1 + RF)}. \]  

(3.13)

If we assume \( \text{prob} \) as the artificial probability that the stock price increases, \( (1 - \text{prob}) \) should be the probability that the stock price decreases, and the value of the option can be computed as the expectation of the payoff discounted by the risk free rate under the assumed probability.
Moreover, given the so defined probability, the correspond expectation of the future return of the stock price is also the risk free interest rate.

\[
prob \times Su + (1 - prob) \times Sd = (1 + R_F)S. \tag{3.14}
\]

This suggests that we can assume that the expected return on the underlying asset equals the risk-free return, under this non-real, artificially defined probability. We then calculate the projected future value of the option and discount it at the risk-free discount rate. This method is called Risk-Neutral Valuation. Under such precondition, the present value of a future cash flow is its expectation discounted by the risk free interest rate.

### 3.6 Options, risk management, and flexible portfolio management.

Suppose that you are the investment manager, and you are only asked to have the possession of one share of the underlying stock at time period 2 discussed in the previous example. And you are offered 119.6$ at the initial time period to make the investment. Meanwhile, as a successful manager, you would like to maximize the final value of the investment with the least possible risk.

One of the easy strategies is just buying a share of the stock at the current price of 100$, and placing the remaining 19.6$ in the bank, and do nothing else during this period. Finally, at time period 2, the investment includes 1 share of the underlying stock, and 23.7$ in the bank saving (future value of 19.6$ with 2 time periods of 10% risk free interest). Considering the stock price uncertainty, the total value of the investment at time period 2
could be 223.7$, 123.7$ or 73.7$, depending on the final stock price.

A question may arise, “What about using the call option?” Since we already computed that the fair value of the call option is 20.4$, we may divide our cash into two parts: the first 20.4$ is used to buy the call option with 120$ strike price, and we put the rest 99.2$ in the bank. At time period 2, the money we put in the bank grows to 120$ exactly. Then we will decide according to the current stock price at time period 2, if the stock price grows up to 200$, we will exercise the option to buy one share of the underlying stock with our 120$ in the bank. If the stock price is 100$ or 50$, we would not exercise the option but buy the stock directly in the market. Thus, the final value of the investment at time period 2 with a call option would be 200$, 120$, and 120$, for the stock prices of 200$, 100$, and 50$ respectively.

Comparing the results of the option strategy and direct strategy shown Table 3.3, both have achieved the requirement of holding one share of the target stock at time period 2. However, the value of the direct strategy has a higher variance than that of the option strategy. The return of the direct investment strategy is 23.7$ higher than the option strategy in the optimistic case, but 47.3$ lower in the worst case. It can be concluded that the option strategy can change the distribution of the return and hedge the risk.

In fact, financial options can be also used to increase the leverage rate by creating a riskier asset (“aggressive strategy”). For example, instead of one unit of option, aggressive investors may choose to buy 5 call options. At time period 2, each option is only worth 80$ if the stock price is 200$, otherwise, the option is valueless. This investment strategy will result in the highest return if the stock price goes up to 200$, with a low return for the
### Investment return structures with different strategies.

<table>
<thead>
<tr>
<th>Investment strategy</th>
<th>Direct investment</th>
<th>Option strategy</th>
<th>Aggressive strategy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total investment</td>
<td>119.6</td>
<td>119.6</td>
<td>119.6</td>
</tr>
<tr>
<td>Portfolio</td>
<td>Bank saving</td>
<td>Stock</td>
<td>Bank saving</td>
</tr>
<tr>
<td></td>
<td>19.6</td>
<td>100</td>
<td>99.2</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>20.4</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>17.6</td>
</tr>
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<td></td>
<td></td>
<td></td>
<td>102</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Value at Time 2</th>
<th>Stock price</th>
<th>Option</th>
<th>Option</th>
</tr>
</thead>
<tbody>
<tr>
<td>High</td>
<td>23.7</td>
<td>200</td>
<td>120</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>80</td>
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<td></td>
<td></td>
<td></td>
<td>21.3</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>400</td>
</tr>
<tr>
<td>Mid</td>
<td>23.7</td>
<td>100</td>
<td>120</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>21.3</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0</td>
</tr>
<tr>
<td>Low</td>
<td>23.7</td>
<td>50</td>
<td>120</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>21.3</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0</td>
</tr>
</tbody>
</table>

Table 3.3: Investment return structures with different strategies.

other situations.

The risk management may be achieved through the use of options, or, at the same time, in another way. As we have discussed for the option pricing model, the call option is priced through a replicating portfolio with the underlying and risk-free assets. Indeed, it also suggests that by proactively managing the portfolio, managers may create the same option even though there is no such option in the market. All that managers need to do is just to trade the underlying and risk-free assets and to create the replicating portfolio according to the realization process of the underlying asset.

### 3.7 Decision making and optimization with flexibility

Now let us go back to the discussion about the decision making process. When using the words “flexible decision”, a fundamental question may raise: What is exactly
flexibility, and how does one distinguish the flexible decisions from the deterministic ones.

In the previous example, if there is a share of the underlying stock in the portfolio, it is considered that the operational action is “deterministic”, since the asset holder will passively receive the payoff affected by the uncertain stock price change. However, if the asset in the portfolio is a European option contact, the operational action is then “flexible”, since the option holder would choose whether to exercise the option depending on the stock price on the expiration date.

If we look deeper into the fundamentals of the European option, it is actually a replicated asset with a dynamic portfolio of both underlying asset and risk free asset. The decision process can be considered as a decision scheme where optimized decisions are made according to the uncertain variables.

For example, Figure 3.5 shows a three-period European put option and its corresponding option price. The starting price of the stock and the strike price of the option are both 100$, the price of the underlying stock could either grow up to 120$ or decrease to 80$. The risk free interest rate is 3% for each time period. The calculation of the option price will follow the same method as the call option. First, the risk-neutral probability can be calculated as 57.5% and 42.5%, for the underlying prices up and down respectively. The payoff at the expiring date depends on whether the option is worth exercising. Finally the option value for each node is calculated as the mean of the expected future payoff under risk neutral probability.

The valuation process suggests that the option holder may make a flexible decision at the option expiration date which helps him/her to avoid the risk of a high underlying
Figure 3.5: Underlying price and option value for a European put option

price (in this case, more than 100$). Meanwhile, a decision scheme for each possible future state is also shown. At each node, the decision (in this example, the replicating portfolio) is determined by an optimization of its uncertain future outcome.

In order to show the relationship between operational flexibility and future uncertainty optimization, Figure 3.6 shows the same three-period put option but of an American type, which means that this put option can be exercised at any time before expiring, since the option holder for American types of options are more flexible in the exercising time. Additional optimization should be performed to decide whether to exercise the option for each time period.

In this example, during time period 2, when the underlying price is 64$, the option holder should choose whether to exercise the option (with an immediate profit of 36$), or to keep the option for the future payoff (the future expectation would be the value of the
European put option, 34.08$). A rational option holder would certainly choose to exercise the option, as a result the correct value of the American put option would be 36$ (if the underlying price is 64$ at the second time period). This can be also explained by the no-arbitrage theory: if the American put option is traded at the same price as the European one (34.08$) with the underlying price at 64$, the market participants would start buying the option and exercise it immediately at the market for profit.

After the comparison between the immediate exercising and holding the option at each time period, the value of the American put option at the starting point can be calculated. It can be observed that the value of American put option is slightly higher than the European one, because it offers more operational flexibility. And the difference in the option value refers to the additional flexibility with the American option.

To answer the question mentioned at the beginning of this section, operational
flexibility is an optimized decision scheme which is a function of the uncertain future outcomes. Two issues are essential for a flexible decision. On the one hand, measures should be modeled in response to the possible future state. In order to define the countermeasures in an uncertain environment, optimization should be performed in order to choose the most appropriate action. On the other hand, future uncertainty should be modeled and considered when performing the optimization.

3.8 From financial options to real options

In the real world, decision makers also face problems including additional decisions or flexible sub-decisions after the uncertainty is resolved. For example, new information may be available in the future and thus a feedback sub-decision should be made to adapt to the changing situation. Meanwhile, a decision maker has the right but not the obligation, like in option theory, to flexibly adapt to further incoming information, by changing the original plan. The real option theory brings the role in the financial option into the strategic decision of the company in order to be flexible in the uncertain environment. The reasoning above implies that the classical static investment budgeting method cannot be used to model the decision or operational process, and more advanced decision making methods are necessary to help managers to analyze the decision process.

The real option method has been developed for valuating investment decisions with operational flexibility as an extension of the financial options to simulate actions on real assets or investments (Trigeorgis, 1996). Comparing financial options and real options, the fundamental real option framework considers the investment project itself as
the underlying asset. The uncertainty is presented as value volatility: in financial options, the price of underlying assets is the main source of uncertainty. And for real options, the value of the project is uncertain in the future. It depends on the uncertain realization of the value of the project, because additional operational options may be available. Table 3.4 illustrates the basic conceptual difference between financial option and real option models (Ruiz López, 1986)

<table>
<thead>
<tr>
<th></th>
<th>Financial option</th>
<th>Real option</th>
</tr>
</thead>
<tbody>
<tr>
<td>Underlying asset</td>
<td>Share</td>
<td>Investment project</td>
</tr>
<tr>
<td>Value of underlying asset</td>
<td>Share price</td>
<td>Project PV</td>
</tr>
<tr>
<td>Exercise price</td>
<td>Exercise price</td>
<td>Required investment</td>
</tr>
<tr>
<td>Exercise date</td>
<td>Expiration date</td>
<td>Depend on project</td>
</tr>
<tr>
<td>Source of volatility</td>
<td>Share prices volatility</td>
<td>Project value volatility</td>
</tr>
</tbody>
</table>

Table 3.4: Comparison of financial option and real option.

As discussed above, whether a real option is available depends on the realization of the uncertain value of the underlying asset, which is the project itself. According to the project performance, project managers can realize different managerial actions to maximize the profit or reduce the risk. In the literature, various types of real options have been extensively discussed. The most representative ones include expand options, abandon options, waiting options, and switching options.

The expand option allows the project holder to expand the scale of the project by adding new capital or real asset investment. Similarly to a call option, if the value of the project is higher than a certain strike price (the project is performing well). Managers will choose to exercise the call option to obtain the extra payoff by additional investment or
following-up investments. In this case, the initial investment leads to future opportunities. However, if the value of the project does not reach the strike line, the option holder will choose not to exercise the following investment. In this case, the cost of the project is limited to the original investment.

The expand option may be easily found in the R&D industries, pharmaceutical industries, computer industries. Despite that the present value of the initial investment may be negative, it gives the option to develop new projects based on the initial investment.

If the project does not perform well, the holder of an abandon option can choose to leave the project and recap the salvage value. The option could be then considered similar to a put option. The option holder only exercises it when the project value is lower than the strike line. This type of option will reduce the loss of an unsuccessful project.

The waiting option allows the project holders to hold their action until the uncertainty is (partially) unfolded. For an investment with high uncertainty, it is profitable to wait until more information is available, and the market uncertainty is reduced. The value of a waiting option comes from the trade-off between the NPV of the project if it is undertaken immediately at the present time, and the possible risk avoided by the waiting.

The switching option offers flexibility in changing the operational strategy according to the current situation. For example, in the mining industry, instead of a constant production rate, the project holders can change their production, supply, and store according to changes in the product price. In the application of hybrid wind-diesel power systems, operational strategies and dispatch schemes should be decided according to the wind speed and demand level.
In a real option model, the operational strategies can be controlled according to the forthcoming information. In order to optimize the action strategies and schemes, a quantitative model is needed to simulate the decision-making process when an option is involved. At the same time, optimizing methods are also necessary to determine the best decision for multi-stage decisions. In the next chapter, we will introduce several methods to quantitatively valuate options and optimize the decision-making process.
Chapter 4

Quantitative decision making and optimization methods

Decision making under uncertainty is a complex matter. As discussed in the last chapter, the application of financial options offers the possibility of managing the risk distribution. By applying the basis of option theory, well designed strategies can be also applied in the real world to optimize the decision making process in an uncertain environment.

In fact, the option pricing model can be considered as a special application of a general decision making process, even for the simplest European options.Apparently, the option holder only needs to use the knowledge of primary-school arithmetic and check if the strike price is higher/lower than the current price in the exercising date. However, the insight of the option is, indeed, a dynamic portfolio management of the replicating asset according to the price changes in the underlying asset.

Considered as a specific decision making problem, optimization theory under un-
certainty is the basis of option pricing models. In the case of simple European options, the optimization is achieved through a comparison between the underlying price and the strike price when it is expired. In another situation, when the financial option has an early-exercise structure, which means that the option holder may choose to exercise the option before the expiring time, the situation is somewhat complicated. The option holders are not interested just in how much money they should pay for the option, but also in which situation they should exercise the option. In other words, the option holder should make an optimal decision about when and whether to use the right given by the option contract, and compare the payoff earned from exercising the option to the value of keeping it and expecting a higher payoff.

As stated by (Merton, 1998),

“—the special sphere of finance within economics is the study of allocation and deployment of economic resources, both spatially and across time, in an uncertain environment. To capture the influence and interaction of time and uncertainty effectively requires sophisticated mathematical and computational tools”. At the same time, these tools should consider both the inter-temporal and uncertainty dimensions of valuation and optimal decision making. Nowadays, numerical methods, including stochastic differential equations, stochastic dynamic programming and partial differential equations have been employed to assessing the value of financial options.

In this chapter, we first introduce some of the quantitative methods for solving simple financial options and more complicated option contracts with path, historical and time dependence. Then we extend our discussions to a general decision optimization process
4.1 Valuation methods for option pricing

4.1.1 Discrete tree model

The discrete tree model is one of the basic methods to solve the value of a simple option, first proposed by (Cox et al., 1979). The typical binomial tree assumes that the price has 2 possible states in the next time interval, either up or down. The probability of the two states of the process is defined so that the final price distribution matches the standard geometric Brownian motion. If we define the price for the next time interval as $S_u$ and $S_d$ with a probability of $prob$ and $(1 - prob)$ corresponding to the up-path and down-path, the $u$ and $d$ could be solved as follows, with the risk neutral assumption:

$$u = e^{\sigma \sqrt{\Delta t}},$$  \hspace{1cm} (4.1)

$$d = e^{-\sigma \sqrt{\Delta t}},$$  \hspace{1cm} (4.2)

$$u = 1/u,\hspace{1cm} (4.3)$$

$$prob = \frac{e^{R_F \Delta t - d}}{u - d}. \hspace{1cm} (4.4)$$
After contrasting the whole tree from the start to the final option expiration time, we have simulated a tree with normal risk with a variation the same as the underlying asset. The next step is to calculate the option value for the expiring date. Finally, the option value for each node in the tree is calculated as:

\[ C = \text{prob} \times C_{Su} + (1 - \text{prob}) \times C_{Sd} \times e^{R_F \times t}. \] (4.5)

This process is then repeated backwards, finally the last value, which is the starting point of the tree, is the analytical solution value.

The accuracy of the method using binomial trees can be increased if we make the time interval \( t \) shorter, which means that we divide the life of the option into smaller time periods, which do not affect the principle of option valuation (replicating the payoff of the option by a replicating portfolio). When the time interval is small enough, we are assuming that the replicated portfolio is adjusted in a continuous way, which is mathematically equivalent to the Black-Scholes approach.

### 4.1.2 Black-Scholes formula

The Black-Scholes formula (Black and Scholes, 1973) is derived to solve continuous option pricing problem, assuming the "ideal conditions" for the stock and option market:

- The short term interest rate is known and constant.
- The stock price follows a random walk with a variance rate proportional to the square of the stock price. The distribution of possible stock prices is log-normal at the end of any finite interval.
The variance rate of the return on the stock is constant.

- The stock pays no dividends.
- The option is "European"
- No transaction costs in trading the stock or the option
- It is possible to borrow any fraction of the price of a security to buy it or hold it, at the short-term interest rate
- No penalties to short selling.

Given $C(s, t)$ as the value of the option as a function of the stock price $s$ and time $t$, the number of options to hedge one share of stock is $1/C_s'$. For a hedged position contains one share of stock long and $1/C_s'$ options short, the value of the position is $s - C/C'_s$. Then the change in the value of the position is $\Delta s - \Delta C/C'_s$.

The Black and Scholes partial differential equations of the option value can be derived as follows, given Ito’s lemma and no-arbitrage assumption $\Delta s - \Delta C/C'_s = (s - C/C'_s) \times R_F \times \Delta t$.

$$\frac{1}{2}C''_{ss} s^2 \sigma^2 + R_F \times s \times C'_s - R_F \times C + C'_t = 0.$$ (4.6)

Finally, the partial differential equation is solved together with the boundary conditions. Note that according to different option conditions, the boundary condition is distinct.

For a European call option, the boundary condition (value when the option ends) is just the option payoff. The partial differential equation of an European option can be solved as follows:
\[ C(S, t) = s \times N(d_1) - Ke^{-RF(T-t)}N(d_2), \quad (4.7) \]

where

\[ d_1 = \frac{\ln \left( \frac{s}{K} \right) + (RF + \frac{\sigma^2}{2})(T - t)}{\sigma \sqrt{T - t}}, \quad (4.8) \]

\[ d_2 = d_1 - \sigma \sqrt{T - t}, \quad (4.9) \]

\( N(d) \) is the cumulative normal probability density function. \( T \) is the expire time, \( t \) is the current time, \( S \) is the stock price, and \( K \) is the strike price.

### 4.1.3 Finite difference model

For options with complex boundary conditions, analytical solutions do not exist for the PDEs (Cortazar et al., 1998). The finite difference model is the alternative numerical mathematical tool for solving the option pricing with complicated boundary conditions. The method, for instance (Schwartz, 1977), first discretizes all the parameters, setting the value space according to the boundary conditions. Then the derivatives are replaced by a finite difference approximation. The partial differential equations are solved backwards using an implicit or explicit method.

Given the Black and Scholes partial differential equations as follows,

\[ \frac{1}{2} C''_{ss} S^2 \sigma^2 + RF \times S \times C'_{s} - RF \times C + C'_{t} = 0. \quad (4.10) \]
At the discretizing stage, the price $S$ and time to maturity $T$ are first discretized into $M$ and $N$ intervals. The value of the option can be considered as a function of $S$ and $T$; a set of nodes is created to represent the value of the option as a two dimensional space with the two variables.

\[ \Delta S = S_{\text{max}} / N, \]  
(4.11)

\[ \Delta T = T / M. \]  
(4.12)

Then the following numerical approximation is used to define the relationship between the nodes.

\[ C'_s = \frac{C_{i+1,j+1} - C_{i+1,j-1}}{\Delta t}, \]  
(4.13)

\[ C''_{ss} = \frac{C_{i+1,j+1} - 2C_{i+1,j} + C_{i+1,j-1}}{\Delta S^2}, \]  
(4.14)

\[ C'_t = \frac{C_{i+1,j} - C_{i,j}}{\Delta t}. \]  
(4.15)

The payoff boundary condition is applied at time $T$, where the option expires. Together with the other boundary conditions, (for example, the option value is 0 for stock price 0, and equals the stock price when it is very high) we could calculate the whole value space by solving the following equation backwards:

\[ a_j H_{i+1,j-1} + b_j H_{i+1,j} + c_j H_{i+1,j+1} = H_{i,j}, \]  
(4.16)
where

\begin{align*}
a_j &= \frac{1}{1 + R_F \Delta t} \left(-\frac{1}{2} R_F j \Delta t + \frac{1}{2} \sigma^2 j^2 \Delta t\right), \\
b_j &= \frac{1}{1 + R_F \Delta t} (1 - \sigma^2 j^2 \Delta t), \\
c_j &= \frac{1}{1 + R_F \Delta t} \left(\frac{1}{2} R_F j \Delta t + \frac{1}{2} \sigma^2 j^2 \Delta t\right).
\end{align*}

(4.17) (4.18) (4.19)

According to (Ben-Ameur et al., 2007), the methods based on trees and finite differences are normally used for option pricing because sometimes there are no analytical formulas for valuating American options, and the two methods mentioned above could be considered as a dynamic programming method - “The pricing of American financial derivatives can be also formulated as a Markov decision process. That is, a stochastic dynamic programming problem.”

4.1.4 Monte Carlo simulation for path-dependent option pricing

Finite difference schemes have the drawback that they cannot easily handle path dependent payoffs or multiple uncertainties. For more complicated cases, option pricing problems can be solved using Monte Carlo simulation. This technique is often applied to handle multidimensional problems to reduce the computational complexity. (Glasserman, 2004) (Álvarez et al., 2010) (Gamba, 2003)

The idea of the method is to simulate the possible underlying asset price paths and then to approximate the behavior of the underlying asset. The value of the option is the expectation of the option value for each path. And in this case the risk-neural assumption also works in the Monte Carlo simulation.

If the option is of American type, it may cause problems for the traditional Monte
Carlo simulations, since a multistage decision making is involved. In each time period, the option holder has the right to decide whether to exercise the option or not. The problem is finally tackled by (Longstaff and Schwartz, 2001), who proposed a Monte Carlo simulation for calculating the value of American options.

According to (Tonkes and Lesmono, 2012) “the value of the option is assessed at discrete points in time by conducting a regression of the option value assessed against the value of the next time step, where the statistically optimal exercise decision is executed at each time step. At its core, the method combines the characteristics of the Monte Carlo approach with the systematic back-stepping technique of discrete stochastic dynamic programming.”

The Monte Carlo method starts with simulating $N$ price paths, each of them begins with the initial time to maturity, assigning a conditional continuation value for each path, and comparing this value with the exercise value to determine when and whether to exercise the option.

Given the value of an option at the maturity date $C_m(S_m)$, where $S_m$ is the price of the underlying asset at time $m$, the continuation value $C_{\text{cond}}$ at the previous time interval is:

$$C_{m-1}(s) = E[C_m(S_m)|S_{m-1} = s].$$  \hspace{1cm} (4.20)

If we approximate the continuation value of a set of basis functions, the approximated conditional value could be as in the following equation:
where \( bf \) is the number of basis functions, \( \beta \) are the coefficients for each basis function, and \( \psi \) is the basis function.

The least-square minimization is applied to obtain the coefficients \( \beta \), by minimizing the expectation of the difference between the approximate conditional continuation value and the real difference as follows:

\[
E \{ (E[C_m(S_m)|S_{m-1}] - \widehat{C}_{cond}^{m-1}(s_{m-1}))^2 \}. \tag{4.22}
\]

Once the conditional continuation value is estimated, we compare the continuation value with the exercise value. If the conditional continuation value is less than the exercise value, we set the value of the previous time interval to the exercise value, in other words, we should exercise the option at that time interval. In contrast, if the conditional continuation value is larger than the exercise value, we should set the value of the previous time interval to either the value of the conditional value or the value of the current time interval. (Giles and Waterhouse, 2009)

Finally, the process is repeated backwards, to save the value for each time interval, and the value is computed as an expectation of the value of the first time interval.

Indeed, real decision makers usually face a problem which may be modeled as an American option. Since the optimal strategy is not known in advance, according to (Cortazar, 2001), most of the standard forward induction methods are not able to correctly find the optimal solution. Monte Carlo simulation and backward induction with additional
state variable are the alternative method to solve these American options, and the later one increases the model complexity.

4.2 General optimization method

In the general optimization theory, simulation and backward induction are definitely not new concepts. In the following part of this chapter, we focus to the typical optimization methods which are also based on the concept of simulation and backward induction, including the stochastic optimization and dynamic programming.

4.2.1 Stochastic optimization

Stochastic optimization or stochastic programming is designed to solve decision making problems when some parameters are uncertain. It is widely applied to solve both theoretical and real-world decision problems. Examples of practise of stochastic programming may be found in a broad range of areas including, but not limited to, financial portfolio management, transportation planning, and energy optimization.

In stochastic optimization models, the objective function and the constraints should be defined as the basic component. Within the constrain range, the stochastic programming model tries find the decision parameter which maximizes or minimizes the objective function, in order to answer the question “which would be the best decision?”

As (Pineda-Morente, 2011) states, the word “stochastic” in this model has to be understood as the opposite of deterministic, which contains a set of available alternatives as the possible uncertain scenarios. In other words, the uncertainty is normally represented
by a set of representative future realizations. The reason to use the scenario approach is because only a few stochastic optimization problems can be solved with the uncertain parameters modeled as continuous probability density distributions. The scenarios “must represent possible states of the world in a future time and each scenario has an associated probability of occurrence and the sum of the probabilities of all scenarios must be equal to one”, and the model to characterize the behavior of the uncertain parameters should provide description as good as possible of the parameters involved in the decision model.

### 4.2.2 Two-stage stochastic optimization

Two-stage stochastic optimization is a typical decision making process with stochastic programming. Two groups of decisions should be made in these two stages. The first group of decisions are those that should be made before the value of the uncertain parameter is known, while the second group decisions may be delayed until partial or total information about the uncertain parameters is available (Pineda-Morente, 2011). The second group of decisions is also referred to as “recourse decisions”, and these decisions are the ones that “provide the decision maker with the opportunity to adapt to each specific combinations of realized parameters together with the decisions made beforehand”.

The sequence of decisions and events in a two-stage stochastic programming can be represented as in Figure 4.1 (adapted from (Pineda-Morente, 2011)). The root note in stage 1 represents the decisions that have to be made facing the uncertainty involved in the optimization problem. The branches represent the plausible scenarios which contain the possible realization of the uncertain variables. After the uncertainty is revealed, the second stage decision has to be made depending on the realization of the uncertain variable, which
is represented by the final nodes; $\omega$ represents the scenario index from one to the total number of scenario sets (Pineda-Morente, 2011).

Figure 4.1: Two-stage decision making with stochastic optimization.

As a short summary, the final objective of the two-stage stochastic programming method is to find the best solution when decision makers are facing problems with uncertainty when they are in the first stage. Therefore, the best decision made on the stage 1 should “be best positioned against” all the possible future development of the uncertain variable in order to make a global optimal solution. In order to find this “best decision”, the outcome of the realization of an uncertain variable, and the corresponding second-stage decision under the given first-stage decision should be both included in the calculation. And finally, the optimal decision on the first stage can be selected among all the candidates, considering that all possible recourse decisions on the second-stage for each candidate have been optimized.
4.2.3 Multi-stage stochastic optimization

The multi-stage stochastic optimization problems extend the two-stage decision process by adding more time periods at which additional decisions have to be made. The multi-stage stochastic programming, therefore, can be used to solve problems following a “decide – observe – decide” sequence pattern. If we note \( x_1, \ldots, x_T \) to be the decisions on each stage from stage 1 to stage \( T \), and \( \zeta_1, \ldots, \zeta_T \) to be the uncertain data revealed gradually over time before each decision stage, the decision process is formed as the following time sequence (Shapiro et al., 2009):

First stage decision \( x_1 \), First stage observation \( \zeta_1 \), Second stage decision \( x_2 \), Second stage observation \( \zeta_2 \), \ldots, Last stage observation \( \zeta_T \), Last stage decision \( x_T \).

Figure 4.2 (adapted from (Pineda-Morente, 2011)) shows a typical decision making process for multi-stage decision making process. We only take the first three-stage decision as an example. As shown in the figure, the branches not only represent a particular realizationship of the uncertain variable between two consecutive stages, but also an inter-relation within the decision process. In other words, the decision made on the third stage does depend on the previous realization of uncertainty and the corresponding decision on the second stage. Having this in mind, the first stage decision will have an impact on both the following decisions at the second and the third stage, but the second stage decision only impact on its own following scenarios and third stage decisions.
4.2.4 Markov decision process

Markov decision processes, named after the Russian mathematician Andrey Markov, is a framework used to optimize the decision process under a specific type of stochastic process – the Markov process. Important mathematical tools to solve the Markov decision problems include dynamic programming, reinforcement learning and other methods.

4.2.5 Markov Process and Markov chain

Before introducing the methodology in solving the Markov decision problems, it is important to formulate the Markov process. As an influential type of stochastic process, the Markov process is such that the future probability density function is only determined by its current states. In other words, if one cannot make better prediction for the future value of the process by knowing more historical states than the prediction based on solely knowing the present states, this process is Markovian. The Markov process has been applied
in practise in many areas dealing with stochastic problems.

For a time series \( X(t) \) with time-dependency, the value of the time series can be measured as \( x_1, x_2, \ldots \) at times, \( t_1, t_2, \ldots \), a joint probability densities can be assumed as presented, (Gardiner, 1986)

\[
\text{prob}(x_1, t_1; x_2, t_2; \ldots).
\] (4.23)

Then conditional probability densities can be also defined as follows

\[
\text{prob}(x_1, t_1; x_2, t_2; \ldots | y_1, \tau_1; y_2, \tau_2; \ldots) = \frac{\text{prob}(x_1, t_1; x_2, t_2; \ldots, \cap y_1, \tau_1; y_2, \tau_2; \ldots)}{\text{prob}(y_1, \tau_1; y_2, \tau_2; \ldots)}.
\] (4.24)

where time series \( Y(t) \) is the known information with values \( y_1, y_2, \ldots \), at times, \( \tau_1, \tau_2, \ldots \).

If we assume an order of the time series, where,

\[
t_1 \geq t_2 \geq \ldots \geq \tau_1 \geq \tau_2.
\] (4.25)

The conditional probability function can be considered as the prediction of the future values \( x_1, x_2, \ldots \), of the time series \( X(t) \) given the knowledge of the past information \( y_1, y_2, \ldots \).

If the process satisfies the Markov assumption, the conditional probability for the future values is determined only by the most recent state of the condition, presented as follows (Gardiner, 1986),

\[
\text{prob}(x_1, t_1; x_2, t_2; \ldots | y_1, \tau_1; y_2, \tau_2; \ldots) = \text{prob}(x_1, t_1; x_2, t_2; \ldots | y_1, \tau_1).
\] (4.26)
An advantage of the Markov process is its powerful definition so that every term in the process can be defined with very simple conditional probabilities, as follows,

\[ \text{prob}(x_1, t_1; x_2, t_2; \ldots | y_1, \tau_1; y_2, \tau_2) = p(x_1, t_1 | x_2, t_2) \ldots \text{prob}(x_{n-1}, t_{n-1} | x_n, t_n)p(x_n, t_n). \]  

(4.27)

As opposed to Markov process with continues variable state space, the definition of Markov chain is widely applied in some literatures as a special type Markov process, when the state is discrete. According to Gross et al (Gross et al., 2013), the Markov chain is only for those Markov processes with both discrete state space and discrete parameter space for some authors. They also classified the Markov process according to its state spaces and type of parameters shown in Table 4.1.

<table>
<thead>
<tr>
<th>Type of Parameter</th>
<th>StateSpace</th>
<th>Continuous</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Discrete</td>
<td>Continuous-parameter Markov Chain</td>
</tr>
<tr>
<td>Discrete-parameter Markov Chain</td>
<td>Continuous-parameter Markov process</td>
<td></td>
</tr>
<tr>
<td>Discrete-parameter Markov process</td>
<td>Continuous-parameter Markov process</td>
<td></td>
</tr>
</tbody>
</table>

Table 4.1: Classification of Markov process

The Markov process and Markov chain has been proved applicable in practise fitting many real world systems with randomness, “including communication systems, transportation networks, image segmentation and analysis, biological systems and DNA science analysis, random atomic motion and diffusion in physics, social mobility, population studies, epidemiology, animal and insect migration, queuing systems, resource management, dams, financial engineering, actuarial science, and decision systems” (Ibe, 2008).
4.2.6 Markov decision optimization

According to (Wu and Zhao, 2010), the Markov decision processes may be considered as an extension of Markov chains: fixed operational actions are added as a state space of the Markov chain with corresponding rewards. Having this in mind, a Markov decision process is transformed to a discrete time stochastic control process. Generally speaking, at each time step, the system state can be defined, the decision maker needs to decide the operational action within the action space of the state. The system state will change to another one following the Markov process, where the probability of changing to a specific future state is only depending on the current system state and operational action (the previous actions and states make no impact). A reward will be assigned to the decision maker as a function of the operational action, the current and future states and the objective of the Markov decision process, and finally achieving the objective of optimizing the operational policy.

Figure 4.3 shows an example of the state space and state transition between two time stages (Song et al., 2000), time stage $t$ and time stage $t + 1$, for a Markov decision process. The state spaces in time stage $t$ and time stage $t + 1$ in this example are composed of $N$ different stages and the decision maker has to decide the operational action, $a$, from a set of available action options at time stage $t$. At time stage $t + 1$, the system jumps to a stage within the stage space at time $t + 1$. This stage changing is a stochastic process according to the original stage at time $t$, and the operational action the decision maker took at time stage $t$. Due to the system uncertainty, an accurate prediction of the changing in system state is unavailable. However, the state transition behavior may be modeled
through a probability transition function. The function is defined as \( \text{prob}(i, j, a) \), where \( i \) is the original state in time stage \( t \), \( j \) is the final state at time stage \( t + 1 \), and \( a \) is the operational action the decision maker chooses at time stage \( t \).

Markov decision processes often include many time stages called "planned horizon" between the time point when the first stage decision is made, to the ending time stage which is the furthest planning period. Well developed algorithms are available to solve the optimal strategy, “which leads to the maximal expected profit over the planning” (Howard, 1970).

In a general profit optimization problem, for instance, the objective is to find the optimal policy that tells the decision maker which action should be taken under which circumstances (Szepesvári and Littman, 1996). Then the value function for an operational...
action, \( \pi \), \( V_\pi \) can be written with the following expression,

\[
V_\pi(x) = R(x, a) + DR \sum_y \text{prob}(x, a, y)V_\pi(y),
\]

(4.28)

where \( R(x, a) \) is the reward function for the operational action \( a \), under state, \( x \), \( \text{prob}(x, a, y) \) is the probability transmission function, and \( DR \) is the discount rate.

Then, a value iteration method, which is “a essentially a backward stochastic dynamic programming problem” (Song et al., 2000), can be applied to solve the problem. Considering \( V_t(i) \) to be the total expected reward for state \( i \) in time period \( t \), the value iteration method searches for the optimal operational action with the optimal value in the action sets.

\[
V_t(x) = \max_a [R(x, a) + DR \sum_y \text{prob}(x, a, y)V_{t+1}(j)].
\]

(4.29)

A terminal value is set for the last planned time stage, the value and the optimal operational policy are then solved step by step recursively from the last time stage to the first one.

It is also worth mentioning that when an expected profit is the objective function, the variance of the expected profit is not yet considered in the objective function. In other words, it is assumed that the decision maker is risk neutral (Wu and Zhao, 2010). When dealing with the risk-averse problems, (Wu and Zhao, 2010) argue that no provision is found for incorporating the risk attitude in the ordinary Markov decision process. The decision makers have to make a slightly different formulation, such as the risk-sensitive Markov decision process model (Howard, 1970), to solve the problem.
4.3 Discussion

It is not surprising to find that the sequential conditional expectation of the future outcome under certain decision has a significant influence on selecting the optimal decisions. Especially for the American type of option, or a more general decision making process, the time at which a decision should be made is not limited to a single time point. In this case, any decision will impact on the following decisions or system states. For an American option holder, to exercise the option now means the option cannot be exercised later, and for multi-stage decision processes, any change in the system states means the future sequential action for other parallel system states is not available.

As discussed, due to the fact that any decision is based on its sequential conditional future outcomes, the correct modeling of these conditional events and values becomes extremely important for any of these decision making models. In the examples presented, the regression based method, scenario simulations, and probability theory are the general methods to calculate the conditional expected future value.

A Monte Carlo simulation combined with regression-based method can be used for the calculation of the conditional expected future outcome. The advantage of this method is the reduction in the computing time, and the capability to deal with the multi-dimensional data. On the other hand, since the key of this approach is the accuracy of the regression model, this method cannot deal with the problem when it is hard to find an appropriate regression model.

The stochastic programming method is based on the analysis of possible scenarios. A simple two stage stochastic optimization can be applied to solve the optimization
problem for the first stage decision. However, operational flexibility inside one scenario is not allowed in this approach. In other words, the decision maker cannot do adjustments inside a scenario.

More operational flexibility can be added together with the increase in the stages using stochastic programming. In this case, the multi-stage stochastic programming method is similar to the Markov decision process model.

The advantage of the Markov decision process combined with probability theory is that the approach generates directly by itself the optimal decision for the entire planning period. The revealing process of the uncertain variable is incorporated together with the decision process with the multi-stage decision process. The decision maker could know the optimal response to the system according to the incoming information. The disadvantage of this method is the computational complexity, and it also requires the system to be characterized as a Markov model.
Chapter 5

Case study: Operational issues for hybrid wind-diesel systems (the San Cristobal Wind Project)

Hybrid wind-diesel power systems have a great potential in providing energy supply for remote communities and facilities. Compared with the traditional diesel systems, hybrid power plants can offer many advantages such as additional capacity, being more environmentally friendly, and potential cost reduction. The O&M of a hybrid power project requires comprehensive knowledge from both technical and managerial points of view. In this chapter, we focus on one of the largest existing hybrid wind-diesel power systems, the San Cristobal Wind Project (Global Sustainable Electricity Partnership (GSEP), 2013). Performance analysis and computer simulations are conducted to illustrate the most representative operational issues. We demonstrate that the wind uncertainty, control strategies,
energy storage, and wind turbine power curve have a significant impact on the performance of the system.

5.1 Presentations and publications arising from this Chapter


5.2 Background

Nowadays, wind power is becoming a widely accepted solution for providing alternative power supply to remote or isolated areas. Many applications and demonstration projects with wind power have been established around the world. Being different than the traditional power systems, the O&M of the new hybrid renewable energy system requires comprehensive knowledge from both technical and managerial points of view.

In order to show some key issues concerned with the management of a hybrid wind-diesel power project, this case study focuses on one of the largest existing wind-diesel energy systems, the San Cristobal Wind Project.

The Galapagos Islands, belonging to the country of Ecuador, are located in the
eastern Pacific Ocean. The islands consist of 18 main islands, 3 smaller islands, and 107 rocks and islets. San Cristobal is one of the four inhabited islands in Galapagos. Before year 2007, three 650 kW diesel generators were used to provide energy supply to the nearly 6 thousand inhabitants with average electricity demand of approximately 900 kW, and peak energy demand at around 1700kW (Kornbluth et al., 2009).

The wind project was developed in the year 2007. After a bidding process, MADE a Spanish company was selected as the wind turbine provider. A total of three 800 kW synchronous type wind turbines without energy storage were installed. The minimum wind speed for the wind turbine starting generating energy is 3.5m/s and it reaches the maximum capacity with a 12m/s wind speed. SANTOS-CMI of Ecuador was selected for logistics and construction. A 12km transmission line, with 3km underground, was also built to connect the wind turbines to the power grid. Finally, in October 2007, the San Cristobal Wind Project was finished and started commercial operation on the island.

This project is based on a Public-Private Partnership framework (the E8 organization, 2008). The Ministry of Electricity and Renewable Energy of the Republic of Ecuador, and Elegalapagos EP, the government-owned electricity utility for the Galápagos islands, are participating as the public Sector. Eólica San Cristóbal S.A. (EOLICSA) are created as the owner and operator of the San Cristóbal Wind Power Project. The company is owned by the San Cristobal Wind Project Commercial Trust with American Electric Power (AEP) and RWE as the “Settlers” and Elegalapagos EP is the Adherent and the Beneficiary. Both AEP and RWE are members of the e8 Fund.
5.3 Financial investment and tariff

The investment for constructing the San Cristobal Wind Project has been approximately $9,840,000, as a global partnership project. The funding of the construction is raised from different sources as shown as Table 5.1.

<table>
<thead>
<tr>
<th>Amount</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$4,850,000</td>
<td>Cash Donation provided by Global 3e, a charitable fund established by e8 members. The majority of the donation was provided by AEP as project leader, with support from RWE, HQ, and ENEL.</td>
</tr>
<tr>
<td>$625,000</td>
<td>Cash donation provided by RWE.</td>
</tr>
<tr>
<td>$930,000</td>
<td>Matching grant donation provided by United Nations Foundation (UNF)*</td>
</tr>
<tr>
<td>$3,195,000</td>
<td>Capital Subsidy provided by Ecuadorian Government (FERUM)</td>
</tr>
<tr>
<td>$240,000</td>
<td>2004 Designated Income Tax Payments by Ecuadorian contributors through Municipality of San Cristobal.</td>
</tr>
<tr>
<td>$9,840,000</td>
<td>TOTAL FUNDING</td>
</tr>
</tbody>
</table>

Table 5.1: Funding for the San Cristobal Project (source: http://www.eolicsa.com.ec/)

The project cost for the San Cristobal Wind Project is higher than other similar wind energy projects in remote areas. According to Hinokura (Hinokuma, 2008), the high cost of construction is mainly due to the logistical and environmental challenges in the Galapagos Islands, lack of infrastructure, and the high diesel displacement objectives of the project. Compared to the other projects, additional costs should be paid for the proper integration of the existing diesel generators to a wind-diesel hybrid system, construction of a 12 km transmission line with 3,000 meter underground, construction of a new access road,
shipping equipment, and environmental issues.

According to the official website of the project (http://www.eolicsa.com.ec/), the San Cristobal Wind Project will receive a fixed tariff of 0.1282$ per kWh for a twelve-year period, with no adjustment for inflation. This tariff is less than the current price paid for the diesel generation in San Cristobal, estimated at 0.1585$ per kWh. Meanwhile, the Wind Project will not impact on the electricity price paid by the consumers (approximately $0.10 per kWh) with the help of the energy subsidy by the Ecuadorian Government.

5.4 Feasibility study

The Feasibility Study was carried out in 2005. Different expected results have been found in the published documents. According to “e8 The Galapagos San Cristobal Wind and Solar Projects” published in 2008 (the E8 organization, 2008), the wind project is expected to significantly reduce San Cristobal’s consumption of diesel fuel. The expected annual performance of the hybrid wind-diesel power system is modeled using the HYBRID2 computer model, developed by the US National Renewable Energy Lab (NREL), the expected result is shown in the Table 5.2.

<table>
<thead>
<tr>
<th>Year</th>
<th>Power Demand (kWh)</th>
<th>Wind Energy Delivered (kWh)</th>
<th>%Diesel Displacement</th>
</tr>
</thead>
<tbody>
<tr>
<td>2008</td>
<td>7,981,164</td>
<td>4,126,164</td>
<td>52%</td>
</tr>
<tr>
<td>2013</td>
<td>10,186,114</td>
<td>4,887,240</td>
<td>48%</td>
</tr>
<tr>
<td>2018</td>
<td>11,808,498</td>
<td>5,375,724</td>
<td>46%</td>
</tr>
<tr>
<td>2023</td>
<td>13,689,286</td>
<td>5,932,941</td>
<td>46%</td>
</tr>
<tr>
<td>2028</td>
<td>15,869,643</td>
<td>6,626,638</td>
<td>42%</td>
</tr>
</tbody>
</table>

Table 5.2: Expected annual power demand and wind energy production by the San Cristobal Wind Project
However, more modest estimations have been found in other documents. According to the Project Design Document of the San Cristobal Wind Project submitted to United Nations Framework Convention on Climate Change (UNFCCC) (San Cristobal Wind Power Project, 2007) in 2007 the project is expected to produce 3,32 GWh in the first year of operation (assuming 52 % kWh annual diesel displacement and 96.5 % wind turbine availability) and to increase generation until 4,43 GWh due to annual increases in electricity demand. During the first crediting period of 7 years, the project activity is expected to generate about 24,93 GWh of energy from the wind power. This estimation claims 37% diesel displacement in the year 2026, with annual wind generation of 4.43GWh. Detailed estimated energy generation by wind energy is shown in the Table 5.3, and Table 5.4

<table>
<thead>
<tr>
<th>Year</th>
<th>Electricity supplied to the grid (kWh/year)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2007</td>
<td>3,316,759</td>
</tr>
<tr>
<td>2008</td>
<td>3,387,240</td>
</tr>
<tr>
<td>2009</td>
<td>3,471,068</td>
</tr>
<tr>
<td>2010</td>
<td>3,555,581</td>
</tr>
<tr>
<td>2011</td>
<td>3,640,671</td>
</tr>
<tr>
<td>2012</td>
<td>3,747,344</td>
</tr>
<tr>
<td>2013</td>
<td>3,816,214</td>
</tr>
</tbody>
</table>

Table 5.3: Estimated energy generation in the first period 2007-2013.

<table>
<thead>
<tr>
<th>Operational Year</th>
<th>Annual Generation (MWh)</th>
<th>Annual Load Increase (%)</th>
<th>Annual Diesel Displacement (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2007</td>
<td>6,590</td>
<td>5.0</td>
<td>52.8</td>
</tr>
<tr>
<td>2011</td>
<td>7,762</td>
<td>4.5 (2008-2011)</td>
<td>48.6</td>
</tr>
<tr>
<td>2016</td>
<td>9,444</td>
<td>4.0 (2012-2017)</td>
<td>44.1</td>
</tr>
<tr>
<td>2021</td>
<td>11,055</td>
<td>3.0 (2018-2021)</td>
<td>40.1</td>
</tr>
<tr>
<td>2026</td>
<td>12,205</td>
<td>2.0 (2022-2026)</td>
<td>37.6</td>
</tr>
</tbody>
</table>

Table 5.4: Estimated Annual Generation (electricity load) and Diesel Displacement
It is worth mentioning that, since the investments involved are mainly donation-based, no report about cash flow payback and profitability is available.

### 5.5 Actual performance

After 6-years operation, EOLICSA has published the report “Galápagos San Cristobal Wind Project: Highlighting 6 Years of Operations” (Global Sustainable Electricity Partnership (GSEP), 2013). Comparing with the real energy generated from the wind turbine with the planned numbers from the feasibility study, a general overestimation is observed in the wind power for all the years. Table 5.5 compares the actual and estimated energy delivered to the grid by the San Cristobal Wind Project. For the five complete accounting years from 2008 to 2012, the wind turbines generate an average of 84% (from 64% to 96%) of the estimated energy. Meanwhile, the wind turbine availability time is 93%, also lower than the expectation of 96.5% in the feasibility study.

<table>
<thead>
<tr>
<th>Year</th>
<th>Estimated electricity supplied to the grid (kWh)</th>
<th>Actual energy generated from wind turbine (kWh)</th>
<th>Actual/Estimated Penetration level</th>
</tr>
</thead>
<tbody>
<tr>
<td>2007</td>
<td>3,316,759</td>
<td>790,398 (Oct-Dec)</td>
<td>Not applicable</td>
</tr>
<tr>
<td>2008</td>
<td>3,387,240</td>
<td>2,682,461</td>
<td>79.2%</td>
</tr>
<tr>
<td>2009</td>
<td>3,471,068</td>
<td>3,204,436</td>
<td>92.3%</td>
</tr>
<tr>
<td>2010</td>
<td>3,555,581</td>
<td>3,434,854</td>
<td>96.6%</td>
</tr>
<tr>
<td>2011</td>
<td>3,640,671</td>
<td>3,344,625</td>
<td>91.9%</td>
</tr>
<tr>
<td>2012</td>
<td>3,747,344</td>
<td>2,398,372</td>
<td>64.0%</td>
</tr>
<tr>
<td>2013</td>
<td>3,816,214</td>
<td>2,453,916 (Jan-Sep)</td>
<td>Not applicable</td>
</tr>
</tbody>
</table>

Table 5.5: Actual and estimated energy generation in the first period 2007-2013
The reason of this under-performance has not been disclosed by the report. More analyses should be carried out in detail in order to correct the over-estimation with more data.

The large volatility of the wind energy production along the time horizon is shown in the report (Global Sustainable Electricity Partnership (GSEP), 2013). In 2010, a maximum level of approximately 3.4 GWh is produced by wind in a year. Compared to the 2.4GWh energy production from wind turbines in 2012, the difference is 1GWh. Meanwhile, a large volatility can be also observed in the monthly performance of the project. Figure 5.1 shows the wind energy penetration of the wind project from Jan, 2008 to Sep, 2013. A clear decrease of penetration happened periodically from Jan to Apr for each year. The average penetration level for the months from Jan to Apr is 13.2%, 42.5% for the other months.

Figure 5.1: Wind energy penetration of the San Cristobal Wind Project from Jan 2008 to Sep 2013
This finding is in accordance with the wind character within the year. Figure 5.2 shows the average wind speed from Jan 2008 to Sep 2013, the wind speed is generally lower from Jan to Apr in each year. The average monthly wind speed from Jan to Apr is 4.4m/s, while the average monthly speed in the other months is 6.7m/s. The average wind speed data also shows that an unusually low-wind year occurred in 2008, which is in accordance with the relative low production in this year. These findings suggest that a long term wind power uncertainty has an important impact on the wind turbine performance, which should be noticed by the researchers.

Figure 5.2: Monthly average wind speed from Jan 2008 to Sep 2013

Clear positive correlation has been observed between the monthly wind energy penetration level and the monthly average wind speed, shown in Figure 5.3. When the monthly average wind speed is lower than 5m/s, the wind penetration level is generally less than 20%. On the other hand, if the average monthly wind speed level is higher than 6m/s, the wind energy penetration level would be expected to be larger than 25%.
The periodical wind speed change and the relationship between wind speed and wind power production do not explain the fact that in 2012, only 2.4MWh energy had been produced by wind energy, even lower than that in 2008, in which an unusually low wind year occurred. Another event mentioned by the report occurred in May 2012, “which resulted in the unavailability of 80 days of one wind turbine and required 2 specialists from the Manufacturer to be on site”. This could explain part of the unusual low production in 2012. The wind energy production in the month of May and Jun was significantly lower, in comparison to the other months. As a result, more accurate analysis on rare events should be included for other hybrid wind-diesel power plants.

Since no energy storage systems are designed to work along with the hybrid system, the operational mode for the power system is based on a diesel-always-on criteria, supervisory control is active in order to keep minimum diesel load (Jargstorf, 2008).
One of the drawbacks of this control strategy is the decreasing fuel efficiency, since the diesel engine is not working at nominal power load. Due to the wind uncertainty, more reserve power should be considered in the case of a sudden drop in wind speed.

In order to solve the problems mentioned above, instead of automatic operation, manual operation has been used with 2 diesel engines constantly working in parallel. Consequently, the efficiency of the fuel consumption of the diesel power generator decreases even more, which will result more unrealistic fuel saving. The possible solution for the diesel engine is to apply advanced power dispatch strategies, taking into consideration both the wind uncertainty and the diesel efficiency.

According to (Jargstorf, 2008), during the first 3 months the wind energy penetration level was 45%. However the fuel consumption of the diesel engine increased from 0.33 to 0.4 liters per kWh, which means that the diesel generation efficiency, went down from 11.45 to 9.31 kWh per gallon. Therefore, the effective fuel saving were only 33% (with a nominal of 45%) in these months. Advanced power dispatch strategy considering both wind uncertainty and diesel efficiency is therefore necessary for future developments.

### 5.6 Performance simulation

Seeking for a detailed analysis about how the related factors will impact on the performance, we use the software HOMER (Hybrid Optimization Model for Electric Renewables) developed by NREL (National Renewable Energy Laboratory, USA), in order to simulate the performance of the San Cristobal Wind Project.

The monthly average wind speed data and the monthly energy demand data from
The year 2011 is used to generate the hourly wind speed and demand series. The demand data are adapted based on the work of Hinokuma (Hinokuma, 2008). The wind turbine character and wind speed response are also simulated. Meanwhile, the operating strategy is adapted as reported by (Jargstorf, 2008), in which 2 of the diesel generators are maintained spinning with a 25% of the rated capacity as the minimum working capacity.

The simulation results are shown in Figure 5.4, indicating that HOMER obtains results similar to those of the real wind penetration level in year 2011. The average absolute error for the simulated penetration level is 3.9%.

In order to validate the simulation with the assumed daily demand, we run the same simulation with the wind speed data and monthly demand data of year 2010, as shown in Figure 5.5, the average absolute error for the simulated penetration level is 3.0%.

Figure 5.4: Simulation result of the wind penetration level in year 2011
Figure 5.5: Simulation result of the wind penetration level in year 2010

The simulation and validation process has shown that the simulation is of significance for managing and optimizing the wind energy delivered by the San Cristobal Wind Project.

Simulation shows the wind energy available in a year is more than 5GWh. However, the wind energy delivered to the grid is approximately 3.3GWh annually for a normal wind year without unusual events.

From the operational experience, according to (Villagómez, 2013), the wind farm of the San Cristobal Wind Project is oversized with the current diesel power plant. The potential improvement based on the current system depends on the available wind energy excess. We simulate the wind energy excess using HOMER for year 2011, as shown in Figure 5.6. Due to the seasonality of the wind speed in the San Cristobal island, the excess
energy also shows a significant seasonality. Most of the unused wind energy is concentrated during the months of high wind speed from May to Nov.

![Figure 5.6: Simulated excess electricity power from wind energy. Example year 2011](image)

The power dispatch scheduling has a significant impact on the wind penetration level. In order to maintain system stability, one of the constraints for the current operational policy is to maintain at least two diesel generators spinning to provide back-up power. The minimum load of the two required diesel generators has a decreased energy gap that could be fulfilled by wind power.

Another possible improvement comes from the energy storage system. The application of energy storage offers the energy producers the ability to shift the energy load (Denholm and Margolis, 2007) (Dorvlo, 2002).

We simulate also the performance by including additional 2500kWh battery storage to the isolated system. The penetration level may be improved approximately in 12% in the high wind season, as shown in Figure 5.7. The wind energy penetration in the low wind
seasons is hardly to be improved, based on the current wind turbines, due to the fact that the potential wind energy excess available in the low wind season is significantly lower than in the high wind seasons. Wind turbines designed especially for low speed wind conditions should be considered in the following development of the next phase of the San Cristobal Wind Project or similar projects.

![Wind penetration level simulation 2011](image)

Figure 5.7: Simulation of system performance with ideal power dispatching and 2500kWh battery storage.

### 5.7 Conclusions

According to the report of “Galápagos San Cristobal Wind Project: Highlighting 6 Years of Operations”, the project is successful in the sense that a positive cash flow has been created to cover the costs of operation and maintenance and other related duties since it started working. This project has been generating an annual revenue of approxi-
mately $400,000, with about 11,000 Certified and Verified Emission Reduction certificates (worth approximately $110,000) as a registered project under the Kyoto Protocol’s Clean Development Mechanism. However, the cash flow is still not enough to recover the high initial investment. A feasibility study must be carried out with more intensive work from a profit/cost point of view.

The high initial cost is one of the most important barriers in constructing and operating hybrid wind-diesel systems. A feasibility study should be carried out with more intensive work from on a profitable basis. Since a general over-estimation has been found for the wind energy delivered to the grid for the San Cristobal Wind Project, more accurate feasibility study methods should be developed in order to provide a better insight into the cash flow and its corresponding operational issues.

Operational issues should be considered when constructing and maintaining a hybrid wind-diesel power system, special events and system failures will cause a considerable loss when operating it. Meanwhile, advanced system control and dispatch technologies are necessary to improve the energy efficiency and maintain system stability and security.

As a short summary, the following aspects should be extracted from the San Cristobal Wind Project

- The feasibility study should be revised in order to avoid biased estimation.
- Wind turbines for low speed wind conditions should be considered to adapt for the low wind season.
- The long term wind resource uncertainty should be taken into consideration.
- Modeling of operational risk and maintenance cost should be considered in
the feasibility study.

- More research should be carried out regarding the application of energy storage to improve the efficiency of the hybrid system.

- Novel dispatching strategies and control modes for diesel engines are necessary to optimize the diesel efficiency.
Chapter 6

Essay: Hybrid wind-diesel power plant optimization with operational options.

A critical problem of a hybrid diesel-wind generation plant is that it may or may not be as profitable as diesel generators alone. In practical terms, project managers also find difficulties in determining the optimal quantity of wind turbines (Honda et al., 2006). The uncertainty of the wind resource is precisely the reason why an optimum operational option policy can be helpful for energy providers to balance energy supply and demand, in order to provide reliable energy and maximize the profit.

In this chapter, a general model is presented based on real option theory and Markov decision process for valuating a hybrid diesel-wind generation plant as an extension of the valuation model proposed by (Honda et al., 2006). A dynamic programming method
is used to generate the optimum operational policy while maximizing the net cash flow of
the plant. The operational option takes into consideration the stochastic nature of the wind
speed on a daily basis, optimizing the option to switch in-line/offline the wind turbine to the
isolated local power grid. Then the optimal quantity scale of wind turbines is calculated
in a practical scenario. This real option model may be applied as a general guide for
valuating and operating a hybrid diesel-wind generation plant. We demonstrate that the
correct utilization of the operational flexibility according to the uncertainty will generate
additional cash flow to the power plant.

The proposed framework expands from previous research the optimization of the
operational policy of the hybrid system. At the same time, given the demand to be covered
by the whole system, the model optimizes the number of wind turbines to be erected on
the site.

6.1 Publications arising from this Chapter


6.2 Background

Discounted cash flow analysis (DCF) is the most widely accepted method for firm
or project valuation and planning. However, the DCF model has shown great inadequacy in
many practical cases since it does not take into account the operational flexibility. Research
work claims that it can lead to under valuation of the project, because it normally assumes
a now-or-never investment. (Martínez-Ceseña and Mutale, 2011) (Pindyck, 1986)

An alternative valuating method is the real option approach. The main difference and advantage is that it also models the available operational action, which is normally flexible from a managerial point of view (Trigeorgis, 1996). Due to its inherent flexible approach, the real option framework also shows significant advantages in the field of operational strategy analysis (Chorn and Shokhor, 2006). Real option models share a lot with operational strategies, providing a value for each operational option in a scenario where decisions are made. As a result, an optimum option can be found in each scenario (Luehrman, 1998a) (Luehrman, 1998b). (Brennan and Schwartz, 1985) developed a real option model for valuating natural resource investments. At the same time, they managed to determine the optimal operational strategy/policy for developing, managing, and abandoning the natural resource project on a yearly basis.

As a result of the characteristics and advantages of the real option approach mentioned above, real option models are increasingly applied to valuate assets/projects with more complexity or uncertainty, such as mining (Brennan and Schwartz, 1985), patents and R&D projects (Álvarez et al., 2010), and renewable energy projects (Venetsanos et al., 2002) (Böckman et al., 2008) (Davis and Owens, 2003) (Siddiqui et al., 2007) (Lee and Shih, 2010) (Siddiqui and Fleten, 2010). Due to market, regulatory and technological changes, especially in the energy industry, the traditional DCF method is no longer sufficient to properly evaluate investments, and researchers are developing several real option models to more precisely encapsulate the flexibility of such projects (Fernandes et al., 2011). According to (Fernandes et al., 2011), real option theories are mainly applied in power generation
investments (Venetsanos et al., 2002) (Böckman et al., 2008), R&D investments/programs (Davis and Owens, 2003) (Siddiqui et al., 2007), and policy evaluation (Lee and Shih, 2010) (Siddiqui and Fleten, 2010) (Yu et al., 2006). However, few of them focus on operational decision making. The authors (Fernandes et al., 2011) also found that there exists a lack of application of this technique in the field of renewable energy, despite the fact that real option models can provide a more realistic valuation in this industry.

Different research works have focused in valuating hybrid generation systems and optimizing their control strategies. (Kaldellis and Kavadias, 2007) develop an expert-type computational algorithm to obtain a cost model considering the installation and the O&M costs. (García and Weisser, 2006) use linear programming and fixed dispatch rule to determine the size of grid units and dispatch for hybrid system with hydrogen storage. (Dufo-López and Bernal-Agustín, 2008) and (Bernal-Agustín et al., 2006) apply multi-objective evolutionary algorithm and a genetic algorithm to find the best combination of components of an isolated hybrid system and control strategies. Kaldellis and Vlachos (Kaldellis and Vlachos, 2006) carry out a detailed energy-balance analysis to predict the optimum hybrid system configuration. (Angarita and Usaola, 2007) optimized the bidding and operational strategy on electricity spot markets for a grid connected hybrid plant. However, current research does not provide the framework to optimize the operational policies. The objective of our analysis is to investigate the relationship between the development of uncertainty and its corresponding optimal operational policy.
6.3 Research objective

Because of the uncertainty linked to the output of wind turbines (it depends on the uncertain nature of wind speed), power supply systems for off-grid communities cannot be based on wind turbines only; a diesel power generator (or a similar stable genset) is needed to provide stable energy supply when wind turbines cannot generate enough energy to meet demand. Moreover, the capacity of the diesel generator is required to be higher than the maximum level of the demand to provide secure, reliable, and stable energy supply. Therefore, the problem is simplified to whether it is profitable or not to combine wind turbines with diesel power supply systems. If the answer is positive, the next step should be deciding the number of wind turbines to install and the optimal operational policy.

The uncertainty of the power output of a wind turbine comes from the uncertain nature of wind speed. Therefore, we construct the real option model by taking the wind speed as uncertain variable.

6.3.1 Probability density function of wind speed distribution

Wind power highly depends on wind speed. Thus, wind speed characterization is essential for estimating wind power generation. Many research works have shown that the wind speed distribution can be well represented by a Weibull distribution (Dorvlo, 2002) (Rehman et al., 1994) (Justus et al., 1978). (Seguro and Lambert, 2000) Their results show that the Weibull distribution can give a relatively good fit representing results when compared to other probability density functions for a wide range of locations and wind climates.
The Weibull distribution is a continuous probability distribution with two parameters, the shape parameter $k$ and scale parameter $\lambda$. The probability density function $\text{prob}_w(s, \lambda, k)$ for wind speed $s$ is:

$$\text{prob}_w(s, \lambda, k) = \begin{cases} (k/\lambda)(s/\lambda)^{k-1}e^{-(s/\lambda)}, & s \geq 0 \\ 0, & s < 0 \end{cases}.$$  

(6.1)

6.3.2 Output function of wind turbine

The output curve of wind turbines can be approximated by using a logistic function or a linear function (between the cut-in wind speed and the cut-out wind speed) (Yu et al., 2006). Figure 6.1 shows typical wind speed to power output curves, where the cut-in wind speed is the speed above which the wind turbines start to generate power, and the cut-out wind speed is the speed above which the wind turbines are switched off in order to protect the wind turbine from high wind speeds.

In this chapter, the logistic model is used to simulate the relationship between the output power and the wind speed. For ease of comparison with other research findings, the logistic function is used the same as that proposed by Honda (Honda et al., 2006), which is given as follows:

$$P(s) = \frac{1}{1/u + b_0b_1},$$  

(6.2)

where $P(s)$ [kW] is the output of a wind turbine, $s$ [m/s] is the wind speed, $b_0$ and $b_1$ are coefficients and $u$ is a scale factor. It is assumed that energy losses are already included in the output function.
6.3.3 Revenue function of wind turbines.

Given the power output function of a single wind turbine, its revenue function at a particular wind speed level during a certain time period can be easily deduced:

\[
CF = \int_{t_1}^{t_2} (P(t) \times E - Cost) dt, \tag{6.3}
\]

where \(CF\) is the revenue, \(t_1\) and \(t_2\) are the starting and ending times, \(E\) [currency/kWh] is the price for electricity power per unit of time, and \(Cost\) is the operational/Maintaining/Operating Cost of a wind turbine per unit of time.

Assuming that, for a discrete time sequence with equal time intervals, the wind speed can be approximated using an average wind speed which follows a Weibull distribu-
tion, the revenue for its corresponding time interval is

\[ CF = P(S_t) \times \Delta t \times E - Cost \times \Delta t, \]

(6.4)

where \( \Delta t \) is the time interval and \( S_t \) is the corresponding average wind speed at time interval \( \Delta t \).

Figure 6.2 shows a typical revenue function for wind turbines. Because of maintenance cost and other costs, the revenue is negative when wind speed is low. Following the increase of wind speed, the revenue starts to increase until it reaches the maximum output rate. When the wind speed is above the cut-out speed, the wind turbine is automatically switched offline. As a simplifying assumption, the maintenance and other costs are neglected when the wind turbine is switched off above cut out wind speed.

![Figure 6.2: Revenue to wind speed curve for wind turbines](image-url)
6.3.4 Switching options and dynamic programming model

To avoid the potential loss of profit due to the operational maintenance costs, especially when wind speed is low, a switching option is provided by offering the chance to switch the wind turbine offline to save the cost of maintaining the generator online. In contrast, the wind turbine can be switched on when it starts generating profit if it was previously offline. For exercising the option, an additional cost should be paid as the switching cost.

In order to value the whole project with switching option and also optimize the operational strategy (when to exercise the switching option), a dynamic programming method is applied.

Before applying the algorithm, firstly the continuous wind speed is discretized into several steps. Then the corresponding probability is calculated for each wind speed level according to the Weibull probability distribution. The Weibull parameters such as the shape factor and scale factor are normally estimated using the local weather statistical information. And finally the probabilities for each level are normalized in the sense that the sum of all probabilities is equal to one. The time interval [0 to T] is also divided into t equal time steps.

In the next step, the dynamic programming algorithm structure is constructed, which will define the optimal operation strategy of the wind turbines. First of all, grids are used to present each switching option which controls each wind turbine. It is assumed that wind speed at time t is known. Thus at each stage of this dynamic process the corresponding energy generated either by wind turbines or by diesel generators can be calculated.
At this point, it is ideally assumed that a part of the diesel generator is linked to each wind turbine, having the same energy capacity as the wind turbine at that point in the grid. The question is: Is it optimal to switch on or off the wind turbine, thus switching off or on the corresponding diesel capacity of the real diesel plant? Here, it is assumed that the diesel plant can supply energy in a continuous way.

To properly address the former question, an additional grid is constructed which represents the difference between the real demand and the flexible energy capacity provided by exercising the options. That is to say, this grid represents the difference between the demand and the energy delivered by the wind turbines or the ideal diesel generators. The values at the nodes of this additional grid represent the remaining energy needed to match demand. This remaining energy has to be provided, by construction, by diesel units of the real diesel plant.

The total energy generated by the diesel plant at that stage is given by the amount of the remaining energy registered in the nodes of the additional grid plus the energy supplied by the ideal diesel generators switched on after evaluating the switching option. Figure 6.3 shows the system configuration.

To evaluate the switching option, a cost function is defined. The two axis of each grid are the time interval and the wind speed. In other words, it ascribes value to the grid nodes at each particular time and wind speed level (which is the underlying). The cost function of the dynamic programming algorithm is the generated cash flow, and the main objective is to maximize it. Since it is assumed that the initial installation cost for the system is known, maximizing the cash flow is actually equivalent to maximizing the final
Figure 6.3: Power supply system framework

value. Figure 6.4 shows the dynamic grids assuming there are M switching options which correspond to M wind turbines.

The dynamic algorithm as presented above assumes that the number of wind turbines is known at the outset. Then the value is solved for each level of wind turbines separately and subsequently the results for finding the optimal quantity scale are compared, as well as the demand for each time interval.

Given a wind speed level, the switching option is to choose either to generate the corresponding energy using wind power or to generate it using diesel fuel. Since it is costly to switch on/off the wind turbines, the value of each switching option depends on whether the corresponding wind turbine is on or off. It also depends on the underlying variable –
the wind speed, which can be used to calculate the cash flow at this particular wind speed level for each status. Other impact factors are the calendar time, t, and the corresponding demand of the particular switching option.

For each switching option, since the corresponding energy at wind speed s is either generated by wind power or by diesel fuel, the value of each option depends on its working status. If a wind turbine is currently online, it can be assigned to working continuously online (in this case, the cash flow in the particular time period is generated from wind energy), or to be switched offline, (in this case, the cash flow is generated from diesel fuel). In contrast, if a wind turbine is offline, it has the same operational option. The optimization process will choose the working status with the highest expected value for each working status. If the value for the following time period and the switching cost are considered, the values of each option are shown in the following equations.
\[ V_{\text{in},t,s,m} = \begin{cases} 
CF_{w,t,s,m} + \frac{1}{1+r} \sum_{s=0}^{\text{max}} V_{\text{in},t+1,s,m} \times \text{prob}_{t+1,s} & \\
CF_{f,t,s,m} + \frac{1}{1+r} \sum_{s=0}^{\text{max}} V_{\text{off},t+1,s,m} \times \text{prob}_{t+1,s} - \text{switch}_1 
\end{cases} \tag{6.5} \]

\[ V_{\text{off},t,s,m} = \begin{cases} 
CF_{f,t,s,m} + \frac{1}{1+r} \sum_{s=0}^{\text{max}} V_{\text{off},t+1,s,m} \times \text{prob}_{t+1,s} & \\
CF_{w,t,s,m} + \frac{1}{1+r} \sum_{s=0}^{\text{max}} V_{\text{in},t+1,s,m} \times \text{prob}_{t+1,s} - \text{switch}_2 
\end{cases} \tag{6.6} \]

where:

- \( V_{\text{in},t,s,m} \) is the Value of the \( m \)th switching option when it is switched online at time \( t \), and wind speed level \( s \),
- \( V_{\text{off},t,s,m} \) is the value of the \( m \)th switching option when it is switched offline at time \( t \), wind speed level \( s \),
- \( t \) is the index of the time interval,
- \( s \) is the wind speed level,
- \( m \) is the index number of the switching option,
- \( \text{prob}_{t+1,s} \) is the probability of wind speed being \( s \) at time \( t \),
- \( r \) is the discount rate corresponding to each time interval \( \Delta t \),
- \( \text{switch}_1 \) and \( \text{switch}_2 \) are the costs of switching offline/inline respectively the wind turbine.

The value of the switching option comes from the trade off in generating the same amount of energy using different energy sources. Therefore it is necessary to estimate the cash flow generated at each particular wind speed level using the two kinds of energy sources: the wind energy (in case the wind turbine is switched on), and in contrast, the diesel fuel
(in case the wind turbine is offline). Note that if the available energy for a particular wind speed is larger than the available demand, there is no profit in generating energy exceeding it, specially in the case when the wind speed level is relatively high, so that a subset of the switching options (the first x options) can fulfill the energy demand, there is no profit coming from keeping the other wind turbines switched on.

If the wind turbine is online, the cash flow it can generate is:

\[
CF_{w,t,s,m} = \begin{cases} 
  E \times \min(D_{rest,t,s,m}; P_s), & 0 < s < cutout \\
  0, & cutout 
\end{cases}
\]  

(6.7)

And if offline, the cash flow to generate the same amount of energy using diesel is:

\[
CF_{f,t,s,m} = (E - F) \times \min(D_{rest,t,s,m}; P_s),
\]

(6.8)

where:

- \( CF_{w,t,s,m} \) is the cash flow generated by the mth wind turbine when it is online, at time \( t \) and wind speed level \( s \),
- \( CF_{w,t,s,m} \) is the alternative cash flow generated using diesel fuel if the mth wind turbine is offline, at time \( t \) and wind speed level \( s \),
- \( E \) is the price of the electricity,
- \( D_{rest,t,s,m} \) is the available demand for the mth wind turbine, which corresponds to the remaining demand after \( m - 1 \) options at time \( t \), if the capacity of the power generator is larger than the demand, there is no profit gained from producing more energy than the available demand, for the first switching option the \( D_{rest,t,s,m} \) is equal to \( Demand_t \).
$P_s$ is the output of wind turbine for wind speed $s$,

$F$ is the cost of fuel per unit of energy,

Thus, if more than one switching option is considered, at each wind speed level, the available demand for the first switching option is the total demand of the corresponding time interval. After each switching option, it is necessary to subtract the available power output from the remaining energy to match demand. This is shown in the following equations:

$$D_{rest,t,s,1} = Demand_t, \quad (6.9)$$

$$D_{rest,t,s,m+1} = \max(0; D_{rest,t,s,m} - P_s), \quad (6.10)$$

where $Demand_t$ is the total demand for time interval $t$.

After having considered all switching options linked to the $m$ wind turbines, the remaining energy needed to match demand (if there is any) shall be generated by the diesel plant, and its cash flows are:

$$CF_{rest,t,s,m} = (E - F) \times D_{rest,t,s,m+1}, \quad (6.11)$$

and the value for the remaining demand for the whole time period is

$$V_{rest,t,s,m} = CF_{rest,t,s,m} + \frac{1}{1 + r} \sum_{s=0}^{\max} V_{rest,t+1,s,m} \times prob_{t+1,s}. \quad (6.12)$$
6.3.5 Valuation and optimal operating policy

Finally, the whole framework of dynamic programming is ready to valuate different operational policy/strategies by back propagation under the assumption that the terminal value at time T is the cash flow generated by each option. The final value of the whole generating system is thus the sum resulting from valuing all the switching options plus the value of the diesel generator linked to the remaining demand.

The operational policy can be optimized by comparing the value for the two statuses \((V_{in} \text{ and } V_{off})\) at each particular wind speed level and time interval. If \(V_{in} - V_{off} \geq switch\), it is optimal to turn the wind turbine online if it was previously offline, and keep it online if it was previously online. If \(V_{off} - V_{in} \geq switch\), it is optimal to turn the wind turbine offline if it was previously online, and keep it offline if it previously was offline.

If the difference between the values of the two situations is less than the switching cost, it is optimal to keep the working status for the corresponding wind turbine.

6.3.6 Deciding optimal quantity scale of wind turbines

The optimal quantity wind turbines is decided by the following process. In order to decide what is the optimal scale of the wind farm, \(m^*\), one should select from among a number of units ranging from 0 to \(M\). Firstly, the model calculates the whole generating system value, at the time period considered, of each quantity \(m\). Secondly, the equivalent cost of each quantity \(m\) can be solved based on the depreciation for the corresponding time period. Finally, the net present value is obtained by subtracting the equivalent cost from the total value and the maximum relative net presents value is obtained. The corresponding
quantity scale is the optimal scale \( m^* \).

In this framework an equivalent cost is used as a means to overcome the fact that the model only optimizes the management of the system for a single year, whereas depreciation and lifetime of the system as a whole, and of wind turbines in particular, extends for at least 20 years.

6.3.7 Summary of the dynamic programming model

The dynamic programming process is applied with the following steps:

- **Step 1**, the time interval is discretized to \( t \) time stages and the wind speed to \( s \) levels. Then the corresponding probability is calculated for each wind speed level, and \( m+1 \) grids are constructed where \( m \) is the number of wind turbines.

- **Step 2**, the model starts at the last time stage \( T \). Considering the first operational option, the cash flow for each wind speed level and each status can be obtained using equations (6.7) and (6.8), then the available power in each wind speed level is subtracted from the total demand using equations (6.9) and (6.10).

- **Step 3**, the algorithm repeats Step 2 for the remaining options, where the available demand is the remaining demand after considering the previous switching options.

- **Step 4**, the cash flow is calculated as generated by the remaining demand after considering all the options, using equation (6.12).

- **Step 5**, the model steps back to time stage \( t-1 \), and starts again from the first switching option. The value at each wind speed level and each status can be simulated using equations (6.6) and (6.5) by taking into account the possible future cash flow while considering the probabilities and the discount rates. As in Step 2, the power generated by
this option is subtracted from the available demand.

- Step 6, Step 5 is repeated for the remaining options, where the available demand is the one remaining after the previous options for time interval t-1.
- Step 7, the model calculates the cash flow generated by the remaining demand after all switching options are considered, for time interval t-1.
- Step 8, this process is repeated backwards (Step 5 to Step 7) until it reaches time step 1, which is the starting point.
- Step 9, the value of the system is solved by calculating the sum of the value of each option and the value of the diesel generation linked to the remaining demand, while optimizing the operational policy of the system.

6.4 **Empirical results**

In this section, the real option model presented with switching options is used to evaluate the implementation of a hybrid diesel-wind generation plant. The results are illustrated using a numerical example based on the data shown by (Honda et al., 2006). The model estimates the value of the installation and optimizes the operational policy. Table 6.1 gives the economical parameters for the two kinds of power generators based on diesel fuel and wind power respectively. The model was programmed using Matlab 8, and the simulation is carried out by a personal computer (AMD Athlon 5200+, 2GB RAM, Microsoft Windows XP). The computation time required was a few seconds for each numerical case.
Table 6.1: Economical parameters of the diesel and wind power plants.

<table>
<thead>
<tr>
<th></th>
<th>Diesel power generator</th>
<th>Wind turbine</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capacity, kW</td>
<td>11000</td>
<td>1500</td>
</tr>
<tr>
<td>Initial cost, million Euro</td>
<td>15.4</td>
<td>3.75</td>
</tr>
<tr>
<td>Operational cost, Euro/h</td>
<td>87.9</td>
<td>6.45</td>
</tr>
<tr>
<td>Fuel cost, Euro/kWh</td>
<td>0.104</td>
<td>0</td>
</tr>
<tr>
<td>Subsidy, million Euro</td>
<td>0</td>
<td>1.25</td>
</tr>
<tr>
<td>Lifetime, year</td>
<td>15</td>
<td>15</td>
</tr>
</tbody>
</table>

The output function of the wind turbines is estimated using the least squares method by (Honda et al., 2006), with a high coefficient of determination, the parameters are $b_0 = 0.54$ and $b_1 = 0.47$, and the cut-in and cut-off wind speeds are $W_i = 3m/s$ and $W_o = 25m/s$ respectively. The demand is assumed to be 6477kW according to the mean electricity demand in Hachijojima from April to September in 2002. The yearly discount rate is 5%, and the energy price in the market is 20yen/kWh. It is assumed that the switching cost is 10Euro to change the operating status of each wind turbine -the same for both switching inline and offline. The probability distribution of wind speed is assumed to be Weibull. Honda (Honda et al., 2006) used the least squares method for estimating the Weibull parameters in Hachijojima, Japan in 2002, results showing that the shape factor is 1.87, and the scale factor is 6.53. In order to compare the results with Honda’s work, the same parameters are used.

Furthermore, in our analysis, the model discretizes the continuous wind speed into 30 steps, corresponding to $0 - 1m/s, 1 - 2m/s, \ldots, 28 - 29m/s, \ldots, 29m/s > 29m/s$. At the same time, an analysis is performed on a daily basis, in other words, the wind turbines can be switched in/off once and only once every day. Given the wind speed of the day based on a one-day-ahead weather report, the operating policy for each individual wind turbine can be
decided, i.e., whether to continue in the operating status or to switch it. The total length of time in our analysis is assumed to be 365 days (one year), and the initial cost of the power generators is depreciated, in such a way that the PV of the sum of the depreciation is equal to the initial cost. Given the quantity scale of wind turbines, the initial cost is not flexible. Finally we calculate the value for each quantity of wind turbines and optimize the operational policy.

Three different scenarios are analyzed: in order to show the impact of operational flexibility in project valuation and compare the result with (Honda et al., 2006), the first two scenarios can be found from Honda. Scenario 1 has a lower wind power abundance level (the real case of Hachijojima, 2002, where $\lambda$ is 6.53 as the scale factor), scenario 2 has a higher wind power abundance (an example case, where $\lambda$ is 8 for the higher wind power scale). In order to validate the proposed method, a more realistic scenario 3 is considered, where the Weibull parameter was estimated monthly by (Torres et al., 2005) for five stations in Navarra (Spain). The wind speed data in Aralar (Spain) is selected as scenario 3, all 3 scenarios are shown in Table 6.2. The cash flow is calculated with different numbers of wind turbines. The results are shown in Table 6.3. (with switching option) and Table 6.4. (without switching option).

So far, only the cash flow from the hybrid diesel-wind generation plant is considered. In order to finally solve the value of the hybrid system, the value of the initial investment is required. Since the lifetime of the power generators is not the same as the time period in our analysis, the initial cost is depreciated equally during its lifetime, and
Table 6.2: Weibull parameter for each scenario.

<table>
<thead>
<tr>
<th>Month</th>
<th>Scenario 1</th>
<th>Scenario 2</th>
<th>Scenario 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jan</td>
<td>8.62</td>
<td>1.46</td>
<td></td>
</tr>
<tr>
<td>Feb</td>
<td>9.5</td>
<td>2.04</td>
<td></td>
</tr>
<tr>
<td>Mar</td>
<td>7.12</td>
<td>1.62</td>
<td></td>
</tr>
<tr>
<td>Apr</td>
<td>7.87</td>
<td>1.88</td>
<td></td>
</tr>
<tr>
<td>May</td>
<td>7.47</td>
<td>2.00</td>
<td></td>
</tr>
<tr>
<td>Jun</td>
<td>6.53</td>
<td>1.87</td>
<td>8.32</td>
</tr>
<tr>
<td>Jul</td>
<td>7.39</td>
<td>1.55</td>
<td>1.85</td>
</tr>
<tr>
<td>Aug</td>
<td>6.79</td>
<td>2.54</td>
<td></td>
</tr>
<tr>
<td>Sep</td>
<td>7.97</td>
<td>2.48</td>
<td></td>
</tr>
<tr>
<td>Oct</td>
<td>7.89</td>
<td>2.27</td>
<td></td>
</tr>
<tr>
<td>Nov</td>
<td>9.48</td>
<td>2.24</td>
<td>2.39</td>
</tr>
<tr>
<td>Dec</td>
<td>9.24</td>
<td>2.39</td>
<td></td>
</tr>
</tbody>
</table>

Table 6.3: Cash flow generated of the hybrid system with switching option. (million Euro)

<table>
<thead>
<tr>
<th>WT number</th>
<th>Scenario 1</th>
<th>Scenario 2</th>
<th>Scenario 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5.7208</td>
<td>5.7208</td>
<td>5.7325</td>
</tr>
<tr>
<td>2</td>
<td>5.8263</td>
<td>6.1141</td>
<td>6.1389</td>
</tr>
<tr>
<td>3</td>
<td>6.0757</td>
<td>6.5703</td>
<td>6.5453</td>
</tr>
<tr>
<td>4</td>
<td>6.3251</td>
<td>6.9006</td>
<td>6.9516</td>
</tr>
<tr>
<td>5</td>
<td>6.5415</td>
<td>7.2031</td>
<td>7.2663</td>
</tr>
<tr>
<td>6</td>
<td>6.6933</td>
<td>7.3806</td>
<td>7.4524</td>
</tr>
<tr>
<td>7</td>
<td>6.8044</td>
<td>7.5016</td>
<td>7.5838</td>
</tr>
</tbody>
</table>

The present value of these equal depreciations is set to be the same as the present value of the total initial cost. Finally the equivalent cost is calculated based on the depreciation.

To find out whether it is profitable to install wind turbines, the model also calculates the value in the case that no wind turbine is installed in the power supply system.

Accounting for the switching options adds a clear and very real value to the model. This becomes explicit when we comparing our results to those of (Honda et al., 2006). Figure 6.5 shows this comparison. Our results (with switching options) are plotted against those of Honda et al. for the first 2 scenarios. The X-axis represents the number of WTs, and
Table 6.4: Cash flow generated of the hybrid system without switching option. (million Euro)

<table>
<thead>
<tr>
<th>WT number</th>
<th>Scenario 1</th>
<th>Scenario 2</th>
<th>Scenario 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5.5393</td>
<td>5.6935</td>
<td>5.7007</td>
</tr>
<tr>
<td>2</td>
<td>5.7687</td>
<td>6.0726</td>
<td>6.0874</td>
</tr>
<tr>
<td>3</td>
<td>5.9905</td>
<td>6.4423</td>
<td>6.4791</td>
</tr>
<tr>
<td>4</td>
<td>6.2159</td>
<td>6.8172</td>
<td>6.8624</td>
</tr>
<tr>
<td>5</td>
<td>6.4216</td>
<td>7.1254</td>
<td>7.1633</td>
</tr>
<tr>
<td>6</td>
<td>6.5314</td>
<td>7.2632</td>
<td>7.3232</td>
</tr>
<tr>
<td>7</td>
<td>6.6201</td>
<td>7.3588</td>
<td>7.4361</td>
</tr>
</tbody>
</table>

the Y-axis represents the relative value of adding wind turbines to the system. The value adding by switching options is also validated in the third scenario with a more realistic wind speed simulation.

![Graph](image)

Figure 6.5: Relative value against number of wind turbines. (10^6 Euro)

The results show that with the switching option, the value of wind diesel hybrid power supply system could be increased. Also the optimal quantity of wind turbines can be decided by the real option model. Furthermore, due to the initial cost of wind turbines, it is not always profitable to combine wind turbines with traditional diesel generators. When the wind power abundance is higher, it is more likely that wind turbines provide positive
value. Considering the quantity level of wind turbines, increasing their number is not always a good choice: an optimal scale exists because of the limitation of demand.

Moreover, an optimum operational policy is determined by the real options model. Figure 6 shows an example curve of the value difference of the 2 status (online/offline) of a specific operational option. Then the model subtracts the offline value from the online value of the option to calculate the value difference. The optimal operating policy can be found for each particular node in the model \((V_{in,m,t,s} - V_{off,m,t,s})\). When the difference between the online and offline statuses reaches the switching cost, it is worth to switch the status to the higher valued one if the wind turbines were previously operated in the other status.

The result shows that for higher wind speed levels (not exceeding the cutoff level) the wind turbine is worth more when it is online because the difference is positive, and for low wind speed levels the wind turbine is worth more when it is offline because the profit it can generate is overshadowed by the relative large maintenance cost. For the extremely high wind speed cases (more than the cut-off wind speed level), since the wind turbine should be shut down, the offline value is of course higher that the online one. In the particular example shown in Figure 6.6, it is optimal to switch off line the wind turbine if the wind is less than 5m/s when it was previously inline; in contrast, it is optimal to switch online the wind turbine if the wind speed is higher than 6m/s when it was previously offline. Clearly the wind turbine should be shut offline when the wind speed is higher than the cut-off speed (25m/s).
In the case of multiple wind turbines, it is not always optimal to keep all the wind turbine online due to the limitation of the demand. Figure 6.7 shows the value difference in the case in which 7 wind turbines are assumed to be implemented in the system. According to the results, the offline-values for a subset of the options are larger than the inline value when wind speed is high, while others are in the opposite situation. This means that in this case it is optimal to switch on only a subset of the wind turbines. Table 6.5. shows the optimal policy corresponding to the wind speed level for the 7 wind turbines case as an example.
<table>
<thead>
<tr>
<th>Wind speed</th>
<th>Optimal number of WTGs inline</th>
</tr>
</thead>
<tbody>
<tr>
<td>0m/s-5m/s</td>
<td>0</td>
</tr>
<tr>
<td>5m/s-11m/s</td>
<td>7</td>
</tr>
<tr>
<td>11m/s-12m/s</td>
<td>6</td>
</tr>
<tr>
<td>12m/s-25m/s</td>
<td>5</td>
</tr>
<tr>
<td>above 25m/s</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 6.5: Optimal operating policy in the seven WTs case.

Figure 6.7: Value difference between the two statuses for operational option in the seven WTGs case. (scenario 1)

Figure 6.8 shows a simulated result using the real option model in a practical scenario. A simulation with a 180-day wind speed series is used to test the framework (Weibull distribution with $\lambda = 6.53$); the real option model is used to determine the operational policy.

6.5 Conclusions

In this chapter, a real option model is applied to value a hybrid wind-diesel power generating system with switching options as well as to decide the optimal quantity of wind
turbines in the system. A consequence of the overall process is that an optimal operational policy is defined. It is shown that the switching option provides operational flexibility to the hybrid power supply system, and that the value can be increased if this operational flexibility is correctly utilized. The results also show that the value of the system depends on the scale of wind speed distribution. An optimal number of wind turbines can be obtained at the outset due to the limitation of demand and local wind power abundance. It is also shown that this value is dependent on the operational policy of the system, and we provide the framework to find the optimal operating decisions.

This real option model framework should be useful not only for project valuation purposes, but also for deciding the operating policy in the long and short term. Future
research work can focus on more specific applications by combining other technologies in the area, such as short term wind speed and demand forecast, reliability analysis, multi-objective design etc, so that the operational flexibility can be accurately addressed. At the same time, more advanced option models need to be developed by taking into consideration other components in the hybrid energy system, including large scale energy storage, other renewable energy sources like solar or hydro power, etc.

The presented model contributes to the state of the art by combining optimal operational strategies for project valuation based on stochastic underlying. The operational cost for changing the working status of the hybrid system was first considered in the valuation model. By applying dynamic programming based on option theory, the research presented in this chapter addresses the additional value when operational flexibility is correctly utilized. It provides an optimized operational strategy in a scenario of multistage decision making. Meanwhile, the proposed model may also be applied to find the optimal scale of installed wind energy, and the valuation of a hybrid plant in the long term.
Chapter 7

Essay: Optimization of diesel dispatching for hybrid systems

A crucial issue when operating a hybrid wind-diesel system is the scheduling and operation of both dispatchable and non-dispatchable energy sources (Bernal-Agustín and Dufo-López, 2009). A smart dispatch strategy may increase the project cash flow by improving the efficiency of the diesel power genset while maintaining the security and reliability of the isolated system. Several factors should be considered when determining the optimal dispatch strategy, mainly the wind power uncertainty and the energy storage system (Luo et al., 2014).

Due to the intermittent nature of wind energy, stochastic models are needed to characterize the power output of wind farms (Morales et al., 2010). Over the last decade, as a result of the rapid development of the wind power industry, wind energy forecasting and modeling techniques have been researched extensively, and several methods can now be
found in the technical literature (see, e.g. (Lei et al., 2009) and (Pinson et al., 2009), and references therein). Thanks to the advanced wind power models, power system managers can perform operational actions using more meaningful and precise information.

The optimal power dispatch of a hybrid wind-diesel power system is path-dependent. This is so because the current state of the storage unit depends on the previous operational actions. As a result, a multi-stage decision process is needed to solve this problem.

In this chapter, a dynamic multi-stage decision-making model is proposed to operate isolated hybrid wind-diesel power systems at minimum fuel consumption. A Markov decision process solved by dynamic programming is applied to determine the system states considering the future uncertainty. The model makes use of a probabilistic characterization of the future uncertain parameters to simulate the potential operation of the wind-diesel system under different conditions. The total fuel cost is minimized at the current time point plus the expectation of the fuel consumption in the subsequent periods.

An illustrative example and a numerical case study is presented for discussion. The result shows that wind power uncertainty has a strong impact on the operating efficiency of the isolated wind-diesel power system. Compared to the deterministic dispatch strategies currently available in the technical literature, the dispatch policy resulting from the proposed optimization model exhibits a remarkable performance in minimizing the total fuel consumption of the wind-diesel system.


7.1 Publication arising from this Chapter


7.2 Background

Today a number of commercial projects for hybrid wind-diesel power systems have been developed to provide power supply to isolated communities in different countries (Baring-Gould et al., 2007). Advanced control techniques have been designed to operate these systems and maintain the voltage (Sebastián and Peña-Alzola, 2015), frequency (Tarkeshwar and Mukherjee, 2015), active power and reactive power (Kassem and Abdelaziz, 2014) within the required limits (Ahmed et al., 2008).

The dispatch strategy is key to control the energy flow within the hybrid system in a cost-effective manner. Traditionally, the power dispatch of hybrid wind-diesel systems is mainly carried out using deterministic tools. In most of the applications and commercial software, including HOMER (Zoulias and Lymberopoulos, 2007) and many other works (Dalton et al., 2008), the dispatch strategy is based on the research conducted by (Barley and Winn, 1996). They propose several control strategies for the dispatch of the diesel generators in a hybrid system. In the “Load Following strategy”, the power from the diesel generator is never used to charge the batteries. In the “SOC (State Of Charge) set-point strategy”, the diesel generator is always running at full capacity, with the aim of charging the batteries until a pre-decided SOC is reached. Finally, in the “Full power strategy”,


the diesel generator runs at full capacity for a prescribed minimum period of time. They argued that by optimally choosing between the “Load Following strategy” and “Full power strategy”, the resulting operational strategy can be virtually as effective as the ideal one.

These dispatch strategies have been widely accepted and applied in feasibility studies (Ma et al., 2014), cost analysis (Goel and Ali, 2014), and project design/planning (Kusakana, 2014) of hybrid wind-diesel systems. Simulation tools have also been developed based on these operational strategies (Bernal-Agustín and Dufo-López, 2009). According to (Bernal-Agustín and Dufo-López, 2009), the most used examples include, but are not limited to, HOMER (Hybrid Optimization Model for Electric Renewables), developed by NREL (National Renewable Energy Laboratory, USA); Hybrid2, developed by the Renewable Energy Research Laboratory of the University of Massachusetts; and iHOGA (improved Hybrid Optimization by Genetic Algorithms), developed by the Electric Engineering Department of the University of Zaragoza, Spain. Some of these softwares can be freely downloaded from their websites.

(Dufo-Lopez et al., 2007) present an improved model to control stand-alone hybrid renewable electrical systems based on genetic algorithms, by including new types of electrical load, and different methods for estimating the lifetime of batteries and storage operation. (García and Weisser, 2006) compare the fixed dispatch rule and a linear programming method on a one-year time series of wind speed data in hourly resolution, and they prove that the linear programming solution outperforms the fixed dispatch rule.

The dispatch strategies mentioned above have not considered the uncertainty in the wind source (Morales, 2010). Optimization methods such as stochastic programming
and stochastic dynamic programming are generally applied in the energy sector to solve the
power scheduling problem including uncertainty. (Garcés and Conejo, 2010) use stochastic
programming to solve the self-scheduling problem for a power producer to maximize the
profit considering uncertain price. Uncertainty is usually modeled using scenario trees
in stochastic programming (Pineda and Conejo, 2010); however, this approach becomes
quickly computationally intractable when dispatch decisions are to be made dynamically in
multiple stages. Lujano-Rojas et al. (Lujano-Rojas et al., 2012) optimize the day-ahead load
management strategy for residential consumers under a real time pricing demand response
program, considering the ensemble forecasting of wind power, electricity prices, etc; however,
a decision scheme for shorter time horizons, for instance hourly-ahead, is still desired. To
overcome these issues, a stochastic dynamic programming approach is applied instead.

Uncertainty modeling and forecasting are fundamental for operational researchers
and engineers to design adaptive decision schemes. In the area of wind energy, a Weibull
distribution is often used to characterize the probability distribution of wind speed from
historical data (Dorvlo, 2002). Point forecasting of wind speed can also be carried out
through a wide variety of methods (Lei et al., 2009). In the last few years, both theoretical
and practical research in the field of wind power forecasts has focused on various forms of
probabilistic forecasting (Pinson et al., 2009), which provide information on the development
of the forecast uncertainty through the forecast series (Morales et al., 2010). Numerical
methods, such as artificial neural network (Lujano-Rojas et al., 2013) and extreme learning
machine (Wan et al., 2014), can be applied to perform a probabilistic forecasting.

When operating a hybrid wind-diesel system, the development of the uncertainty
is essential to model the plausible evolution of the system in the subsequent time periods over the scheduling horizon. Advanced optimization methods are therefore necessary to make the best use of the novel probabilistic forecasting techniques (Pinson et al., 2009), where stochastic dynamic programming has a great potential.

According to (Madaeni et al., 2013) dynamic programming approach has been implemented to estimate the capacity value of energy storage, and capture the effect of system shortage events in subsequent periods. It can be also applied to optimally charge an electric vehicle under the uncertainty inherent to its use (Iversen et al., 2014).

A dynamic programming method is proposed in this chapter to optimally determine the diesel power output for a hybrid wind-diesel power system. Compared to the aforementioned methods, we provide a practical simulation of the actual decision-making process, because the plausible future realizations of the stochastic variables are updated with new information every time a dispatch decision is made. Thus, a customized dispatch scheme can be generated and adjusted dynamically according to the time evolution of the uncertain factors.

### 7.3 Research settings

#### 7.3.1 System description

The isolated hybrid wind-diesel power system shown in Figure 7.1 is used to explain the dispatch strategy proposed in this chapter. The diesel engine and the wind turbines are the main energy sources connected to a remote community. The diesel engine is of the synchronous type, and acts as the main dispatchable energy source. The power production of
wind turbines, which are modeled as non-synchronized AC machines, is treated as a negative load. A bi-directional AC/DC power converter is used to connect an energy storage unit (a battery) to the AC grid. An AC synchronous machine is driven by a DC motor which controls the energy exchanged from the storage to the power grid. The system voltage and frequency are controlled only by the synchronized diesel engine or the AC machine connected to the storage.

Figure 7.1: Example of isolated hybrid wind-diesel power system.
7.3.2 Net load modeling and conditional probability of the net load

In each time period, the net load, \( L_t \), is equal to the electricity load from the grid, \( L_t^e \), minus the wind energy generated by the wind turbines, \( L_t^w \). The net load can be either positive or negative. The positive net load should be supplied by the diesel power unit and/or the stored energy from the battery.

\[
L_t = L_t^e - L_t^w. \tag{7.1}
\]

The net load uncertainty is modeled as a first-order Markov process. This means that the conditional probability \( Q_{t+1} \) of the net load at time \( t + 1 \), \( L_{t+1} \), being equal to \( l \), only depends on the net load, \( l_c \), at the current time period \( t \), that is,

\[
Q_{t+1}(l|l_c) = \text{prob}(L_{t+1} = l|L_t = l_c). \tag{7.2}
\]

7.3.3 Cost functions for diesel engine

The aim of the proposed dispatch model is to minimize the total operating cost of the wind-diesel power system, which includes the fuel cost, the start-up/shut-down cost and the maintenance cost of the diesel power generator.

According to (Barley and Winn, 1996), the function that describes the fuel consumption of the diesel engine can be represented as a linear function of its power output, i.e.,

\[
F = F_0 + F_i \times P, \tag{7.3}
\]

where \( F_i \) is a constant expressing the amount of fuel needed to generate one unit of electrical
power, $F_0$ is the fuel used to maintain the engine spinning, which is proportional to the rated power of the diesel power generator, and $P$ is the power output of the diesel engine.

The maintenance cost of the diesel unit is modeled as a constant cost incurred whenever the diesel power generator is operating. The total cost can be then written as follows

$$C(P) = C_f \times (F_0 + F_i \times P) + C_m; \quad (7.4)$$

where $C_f$ is the fuel price and $C_m$ is the cost of maintenance. By adding up the maintenance cost, $C_m$, and the fuel cost to keep the diesel engine spinning, $(C_f \times F_0)$, the cost function can be rearranged as

$$C(P) = C_i \times P + C_r; \quad (7.5)$$

where $C_i = (C_f \times F_i)$ is the incremental cost for generating an additional unit of power, and $C_r = C_m + (C_f \times F_0)$ is the total cost for maintaining the diesel engine working.

According to the cost function described above, it is clear that the cost per unit of power generated by the diesel generator is lower when the engine is working at a higher load than when it is working within a low load range. This is due to the constant fuel and maintenance costs to keep the engine spinning. Indeed, if we rewrite Equation (7.5) as

$$\frac{C(P)}{P} = C_i + \frac{C_r}{P}; \quad (7.6)$$

one can actually see that there is an economy of scale in increasing the power production of the diesel engine.

The total operating cost for each time period is directly related to the working
status of the diesel power generator and its power output $P_t$, i.e.,

$$C_t(P_t) = C_i \times P_t + C_r. \quad (7.7)$$

On the other hand, to ensure that the power demand is fully supplied by the wind-diesel power system, a sufficiently high cost of load shedding is to be imposed, as shown in Equations (7.8) and (7.9).

The set of possible storage level is denoted as $S$, the storage level available at time period $t$ as $S_t \in S$, the set of possible net loads as $L$, and the net load at time period $t$ as $L_t \in L$. The cost function of the wind-diesel power system is thus the following.

When $P_t = 0$ (i.e., the diesel engine is off-line),

$$C_t(L_t, S_t, P_t) = \begin{cases} 0, & S_t \geq L_t \\ +\infty, & S_t < L_t. \end{cases} \quad (7.8)$$

Otherwise,

$$C_t(L_t, S_t, P_t) = \begin{cases} C_i \times P_t + C_r, & S_t + P_t \geq L_t \\ +\infty, & S_t + P < L_t. \end{cases} \quad (7.9)$$

Finally, it is assumed that a constant cost $X_c$ is incurred every time that the diesel power generator is started up or shut down, i.e.,

$$X(P_{t-1}, P_t) = \begin{cases} X_c, & P_{t-1} = 0 \text{ and } P_t > 0 \\ X_c, & P_{t-1} > 0 \text{ and } P_t = 0 \\ 0, & \text{otherwise}, \end{cases} \quad (7.10)$$

where $X$ is referred to as the switching cost.
### 7.3.4 State transition function of the storage unit

The amount of energy stored in the battery at time \( t + 1 \), \( S_{t+1} \), depends on the storage level at time \( t \), \( S_t \), and the corresponding charging or discharging actions, i.e.,

\[
S_{t+1}(L_t, S_t, P_t) = S_t + S_c^t - S_d^t,
\]

where \( S_c^t \) and \( S_d^t \) are the amount of energy charged into or discharged from the storage device at time period \( t \), respectively. The charging and discharging variables \( S_c^t \) and \( S_d^t \) are functions of the net load and the working status of the diesel generator at time \( t \).

The difference between the net load and the diesel power output is balanced by the storage device. More specifically, if we denote the round-trip energy efficiency of the storage device by \( \eta \), we have the following.

When \( P_t \) is not equal to 0,

\[
\begin{align*}
S_c^t(L_t, P_t) &= \begin{cases} 
\eta \times (P_t - L_t), & P_t - L_t \geq 0 \\
0, & P_t - L_t < 0,
\end{cases} \\
S_d^t(L_t, P_t) &= \begin{cases} 
0, & P_t - L_t \geq 0 \\
L_t - P_t, & P_t - L_t < 0.
\end{cases}
\end{align*}
\]

Else, when \( P_t \) is equal to 0 (the diesel generator is off-line),

\[
\begin{align*}
S_c^t(L_t, P_t) &= 0, \\
S_d^t(L_t, P_t) &= \begin{cases} 
L_t, & L_t \geq 0 \\
b, & L_t < 0,
\end{cases}
\end{align*}
\]

where constant \( b \) represents the energy consumption required for the synchronized AC machine connected to the storage device to provide frequency and voltage control services.
Finally, the energy level of the storage system is constrained to be within the range

$$0 \leq S_t \leq S_{upper}, \forall t,$$

(7.16)

where $S_{upper}$ is the capacity of the storage device.

### 7.3.5 Dynamic Programming Solution Approach

Let $P_t^* \in \mathbf{P}$ be the diesel power output that results in minimum cost (i.e., the optimal dispatch decision at time $t$), where $\mathbf{P}$ is the set of all feasible power outputs. The diesel power output $P_t^*$ is the solution to the following optimization problem:

$$V_t^*(L_t, S_t, P_{t-1}) = \min_{P'} \{V_t^b(L_t, S_t, P') + X(P_{t-1}, P') | P' \in \mathbf{P} \},$$

(7.17)

$$P_t^*(L_t, S_t, P_{t-1}) = \arg \min_{P'} \{V_t^b(L_t, S_t, P') + X(P_{t-1}, P') | P' \in \mathbf{P} \},$$

(7.18)

where $V_t^*$ is the optimal value at time $t$ (in our case, the total operating cost of the isolated wind-diesel power system at time $t$) given $(L_t, S_t, P_{t-1})$, $V_t^b$ is the cost associated with a certain dispatch decision $P'$ made at time $t$, and $X(P_{t-1}, P')$ denotes the cost of changing the diesel engine working status from $P_{t-1}$ to $P'$.

The value associated with a given dispatch decision $P_t$, $V_t^b$, is the operating cost incurred at time $t$ plus the expectation of the future operating cost conditional on implementing $P_t$, that is,

$$V_t^b(L_t, S_t, P_t) = C_t(L_t, S_t, P_t) + E[V_{t+1}^b(L_{t+1}, S_{t+1}, P_t)],$$

(7.19)

where $S_{t+1}$ is the storage level conditional on $P_t$. 
The optimization problem (7.19) is solved numerically by discretizing the continuous variables. According to Equations (7.2), (7.17) and (7.19), if it is assumed that the net load, \( l \) and \( L_t \), and the diesel power output, \( P^t \), take discrete values in the sets, \( L \), and, \( P \), respectively, the optimization problem (7.17) can be rewritten as follows:

\[
V^*_t(L_t, S_t, P_{t-1}) = \min_{P^t} \{ C_t(L_t, S_t, P^t) + \sum_{l \in L} Q_{t+1}(l|L_t) \times V^*_t(l, \tilde{S}_{t+1}, P^t) + X(P_{t-1}, P^t)|P^t \in P \}.
\] (7.20)

Optimization problem (7.20) can now be solved through a backward recursive process, where the energy stored in the battery at time \( t + 1 \), \( \tilde{S}_{t+1} \), can be computed from (7.11) - (7.16), given \( L_t \), \( S_t \), and \( P^t \).

7.4 Illustrative example

In this section, we use a small example to illustrate the proposed procedure for the optimal operation of the isolated hybrid wind-diesel power system.

In order to implement the proposed optimization method in a tractable way, the time horizon index \( t \), the energy level of the storage \( S_t \), the net load \( L_t \), and the power output of the diesel engine \( P_t \) (variable to be optimized), are considered as discrete.

More specifically, we discretize the optimization horizon in four hourly periods, \( (t = 1, 2, 3 \text{ and } 4) \). The net load is approximated by three plausible scenarios, namely, “High”, “Medium”, and “Low”, for each time period, as shown in Table 7.1.

The transition probability matrix that characterizes the net load as a first-order Markov process is given in Table 7.2. For example, if the net load is “High” at time \( t \), then
at time $t + 1$, there is a 50% chance that the net load remains “High”, and another 50% chance that the net load changes to “Medium”.

The power output of the diesel generator is discretized into three values, namely, 0 kW, 200 kW and 400 kW, which correspond to all the possible values of the net load. Likewise, three possible energy storage levels, 0 kWh, 200 kWh, and 400 kWh, are considered. For the sake of illustration and simplicity, we do not consider here the energy lost in the storage process, the energy for regulating the power grid, the switching cost of the diesel generating unit, or a limit on the maximum power output of the energy storage device.

A penalty is added to the cost function when the sum of the total power generated by the diesel engine and the amount of energy contained in the storage is not enough to meet the positive net load. This penalty, together with the operating cost function of the diesel engine, is shown in Table 7.3.

<table>
<thead>
<tr>
<th>Net load (kW)</th>
<th>High</th>
<th>Medium</th>
<th>Low</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time period</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>200</td>
<td>0</td>
<td>-200</td>
</tr>
<tr>
<td>2</td>
<td>400</td>
<td>200</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>200</td>
<td>0</td>
<td>-200</td>
</tr>
<tr>
<td>4</td>
<td>400</td>
<td>200</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 7.1: Net load scenarios in each time period

<table>
<thead>
<tr>
<th>Time t</th>
<th>High</th>
<th>Medium</th>
<th>Low</th>
</tr>
</thead>
</table>
| Time t+1
High    | 1/2  | 1/3    | 0   |
| Medium | 1/2  | 1/3    | 1/2 |
| Low    | 0    | 1/3    | 1/2 |

Table 7.2: Transition probability matrix for the net load
Table 7.3: Operating cost function of the diesel engine and the cost of shedding load

<table>
<thead>
<tr>
<th>Diesel power output</th>
<th>Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 kW</td>
<td>$0</td>
</tr>
<tr>
<td>200 kW</td>
<td>$10</td>
</tr>
<tr>
<td>400 kW</td>
<td>$15</td>
</tr>
<tr>
<td>Load Shedding</td>
<td>$1000</td>
</tr>
</tbody>
</table>

A backward recursive algorithm is applied to solve the dynamic programming problem. In the final time period of the optimization horizon (Time 4), we select the set of dispatch decisions (power output of the diesel engine) that minimize the operating cost for each possible combination of the energy storage level and the net load. These are the ones corresponding to the numbers in parentheses in Table 7.4. In plain words, we consider that the world ends after time period 4. As a result of this assumption, the optimal dispatch strategy in the final time period is to use as much energy in the storage as possible and cover the remaining net load with diesel power. In practice, the time horizon can be chosen as to coincide with the life time of the system or follow a rolling horizon process (Iversen et al., 2014). Note that a penalty of $1000 is applied when the diesel power plus the available stored energy cannot fully supply the net load. For example, in the left-top block in Table 7.4 with a net load of 400 kW and 0 kWh of energy stored, the penalty is charged when the diesel power is set to be 0 kW or 200 kW.

At Time 3, the decision maker should consider the fact that the selected dispatch strategy may impact on the operating cost at Time 4. To be more precise, the storage state at Time 4 depends on the dispatch decision made at Time 3. Table 7.5 shows the final
For instance, if the net load at Time 3 is 200 kW, and the energy storage level in the beginning of Time 3 is 400 kWh (the right-top block in Table 7.5), the storage state after Time 3 should be 200 kWh, if we choose to shut down the diesel power generator, because the net load of 200 kW must be supplied by the battery. In contrast, if we decide...
to dispatch the diesel engine at 200 kW, then the storage state does not change at Time 3. Finally, if the diesel power output at Time 3 is set to 400 kW, the storage status does not change either, since the battery is already fully charged.

In the case of a negative net load (the third block of rows in Table 7.5), if the diesel generator is off-line, the storage cannot be charged with the excess of wind power production, because the storage device should remain in discharging mode to provide voltage and frequency control. As a result, the storage status remains the same, and the surplus of wind power production must be curtailed/spilled. If the diesel engine is, instead, switched on, the storage is charged until it reaches its maximum capacity.

We denote $\tilde{S}_4 = S_4(L_3, S_3, P')$ as the storage level at Time 4 conditional on $L_3$, $S_3$ and $P'$.

We now assign a value $V^b_3(L_3, S_3, P')$ to each possible combination of net load, $L_3$, storage level, $S_3$, and diesel power output $P'$ at Time 3. For this purpose, we use Equation (7.19), i.e., the value associated with the vector $(L_3, S_3, P')$ is equal to the sum of the cost of operating the diesel engine at $P'$ plus the expectation, over the three possible scenarios of net load $L_4$ at Time 4, of the cost of optimally operating the hybrid wind-diesel system for $t > 3$ (that is, at Time 4), given that implementing the dispatch decision $P'$ leads to the storage level $\tilde{S}_4$ indicated in Table 7.5.

The next step is to calculate the cost value of the dispatch options, $V^b_3(L_3, S_3, P')$, based on Equations (7.17) and (7.19). Since we do not consider the switching cost, $X(P_{t-1}, P') = 0$, we have that

$$V^b_3(L_3, S_3, P')$$
\[ = C_3(L_3, S_3, P') + \sum_{l} Q_4(l|L_3) \times V_4^*(l, \tilde{S}_4, P') \]
\[ = C_3(L_3, S_3, P') + \sum_{l} Q_4(l|L_3) \times \min_{P'} \{ V_4^*(l, \tilde{S}_4, P') | P' \in P' \}. \]

Table 7.6 includes the values assigned to all possible combinations of \( V_3^h(L_3, S_3, P') \). The optimal dispatch \( P_3^* \) of the diesel engine at Time 3 for each possible state \((L_3, S_3)\) of the hybrid wind-diesel system is then obtained. The numbers in parentheses in Table 7.6 correspond to the optimal values.

For example, the value \( V_3^h(200, 200, 0) \) is given by \( C_3(200, 200, 0) = 0 \) plus the expectation of the future cost value at Time 4. The conditional probability for a 200 kW net load at Time 3 indicates that the net load at Time 4 has a 50% chance of being 400 kW and another 50% chance of being 200 kW. Meanwhile, since the diesel power output \( P' \) is 0, the conditional storage level at the next time period \( \tilde{S}_4 \) is 0. As a result, the expected conditional value is \( V_4^*(400, 0, 0) \times 0.5 + V_4^*(200, 0, 0) \times 0.5 = 0.5 \times 15 + 0.5 \times 10 = 12.5 \).

Therefore, the cost value \( V_3^h(200, 200, 0) = 0 + 12.5 = 12.5 \). After calculating \( V_3^h(200, 200, P') \) for all the possible diesel output levels \( P' \), the optimized dispatch scheme for Time 3 with net load, \( L_3 = 200 \), and storage level, \( S_3 = 200 \), can be determined as follows:

\[ V_3^*(200, 200, P_2) = \min_{P'} \{ V_3^h(L_3, S_3, P') | P' \in [0, 200, 400] \} = \min\{[12.5, 15, 15]\} = 12.5 \text{ for all } P_2 \in P. \]

with \( P_3^*(200, 200, P_2) = \arg\min_{P'} \{ V_3^h(L_3, S_3, P') | P' \in [0, 200, 400] \} = 0 \text{ kW, for all } P_2 \in P. \]

The algorithm follows in a backward recursive manner until the dispatch strategy
Table 7.6: Dispatch option values $V^b_3(L_3, S_3, P')$ in $\$ at Time 3 and conditional future storage status $\tilde{S}_3$ in kWh at Time 4 (column "Status"), the numbers in parentheses indicate the optimal strategies at Time 1 is determined. Table 7.7 and Table 7.8 show the dispatch actions and their associated values for each possible state of the system at Time 2 and 1, respectively. Finally, the diesel power dispatch strategy at Time 1 is determined similarly by comparing the value of the available operational options for all possible states.

Table 7.7: Dispatch option values $V^b_2(L_2, S_2, P')$ in $\$ at Time 2 and conditional future storage status $\tilde{S}_2$ in kWh at Time 3 (Column "Status"), the numbers in brackets indicate the optimal strategies.

Note that the optimal dispatch actions are slightly different at Time 1 (Table 7.8)
Table 7.8: Dispatch option values $V^b_1(L_1, S_1, P')$ in $\$$ at Time 1 and conditional future storage status $S_2$ in kWh at Time 2 (column "Status"), the numbers in parentheses indicate the optimal strategies.

<table>
<thead>
<tr>
<th>Storage status</th>
<th>0 kWh</th>
<th>Status 200 kWh</th>
<th>Status 400 kWh</th>
<th>Diesel power</th>
</tr>
</thead>
<tbody>
<tr>
<td>Net load</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>200 kW</td>
<td>1000</td>
<td>(24.72) 0</td>
<td>(17.64) 200</td>
<td>0 kW</td>
</tr>
<tr>
<td></td>
<td>34.72</td>
<td>27.64 200</td>
<td>19.72 400</td>
<td>200 kW</td>
</tr>
<tr>
<td></td>
<td>(32.64) 200</td>
<td>(24.72) 400</td>
<td>24.72 400</td>
<td>400 kW</td>
</tr>
<tr>
<td>0 kW</td>
<td>(18.70) 0</td>
<td>(12.31) 200</td>
<td>(6.48) 400</td>
<td>0 kW</td>
</tr>
<tr>
<td></td>
<td>22.31</td>
<td>16.48 400</td>
<td>16.48 400</td>
<td>200 kW</td>
</tr>
<tr>
<td></td>
<td>21.48</td>
<td>21.48 400</td>
<td>21.48 400</td>
<td>400 kW</td>
</tr>
<tr>
<td>-200 kW</td>
<td>13.47</td>
<td>(6.39) 200</td>
<td>(2.64) 400</td>
<td>0 kW</td>
</tr>
<tr>
<td></td>
<td>(12.64) 400</td>
<td>12.64 400</td>
<td>12.64 400</td>
<td>200 kW</td>
</tr>
<tr>
<td></td>
<td>17.64</td>
<td>21.39 400</td>
<td>17.64 400</td>
<td>400 kW</td>
</tr>
</tbody>
</table>

Table 7.8: Dispatch option values $V^b_1(L_1, S_1, P')$ in $\$$ at Time 1 and conditional future storage status $S_2$ in kWh at Time 2 (column "Status"), the numbers in parentheses indicate the optimal strategies.

and at Time 3 (Table 7.6). For instance, given the same situation with $-200$ kW net load and $0$ kWh in the storage, the optimal diesel power output for Time 3 is $0$ kW, but for Time 1, it is $200$ kW. This is due to the terminal condition, which assumes that the stored energy cannot be used after Time 4. In any practical application, this effect should be considered.

### 7.5 Numerical case study

In this section, the proposed method has been implemented and tested with realistic parameters. We use hourly power output data of a wind farm to model the dynamics of the wind power production. The results are compared out-of-sample with those obtained with the predefined dispatch policies suggested in (Barley and Winn, 1996).

#### 7.5.1 Modeling of the Net Load Uncertainty.

When implementing the proposed dispatch strategy, the uncertainty in the net load is modeled as a first-order Markov process. Two factors, the wind power and the electricity
Figure 7.2: Wind-rose of the normalized power output of the data sample

demand, should be considered in generating the data set and modeling the uncertainty.

On the one hand, power output data from a real wind farm, downloaded at Technical University of Denmark, are used to model the dynamics of the wind power production. The time-series data contain 37,583 samples, measured from January 1, 1999 to April 30, 2003 on an hourly basis. Some wrong measurements have been smoothed out based on the nearest data sample. Figure 7.2 shows the normalized wind power output of the data sample in a wind-rose chart.

On the other hand, it is common that energy utilities issue load forecasts covering
the following scheduling period (normally daily); examples can be found at Red Eléctrica de España, REE, where day-ahead point forecasts of power demand are used as input to a power scheduling tool. It is assumed that the daily load profile shown in Table 7.9 as an example of the forecasted energy consumption level in the isolated power system. Random Gaussian noise, $N(0, 2)$ in kWh, is added to this load profile to simulate the real-time energy consumption. The Mean Absolute Percentage Noise, MAPN, is 3.4%. It is comparable to the Mean Absolute Percentage Error, MAPE, of the forecasted hourly energy load, 3.7%, obtained by REE for the El Hierro Island (a hybrid wind diesel power system located in the Canary Islands, Spain) in July 2014. A simulated demand series is then generated with the same size of the wind power data to obtain a dataset with wind power and load data for uncertainty modeling.

<table>
<thead>
<tr>
<th>Time of the day</th>
<th>Energy Load (kW)</th>
</tr>
</thead>
<tbody>
<tr>
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<td>25</td>
</tr>
<tr>
<td>7:00-9:00</td>
<td>65</td>
</tr>
<tr>
<td>10:00-11:00</td>
<td>85</td>
</tr>
<tr>
<td>12:00-17:00</td>
<td>75</td>
</tr>
<tr>
<td>18:00-21:00</td>
<td>95</td>
</tr>
<tr>
<td>22:00-24:00</td>
<td>55</td>
</tr>
</tbody>
</table>

Table 7.9: Daily electricity load profile of the hybrid wind-diesel power system

The uncertainty in the net load, $L_t = L^e_t - L^w_t$, of the system is computed from the wind power output dataset with the daily load with noise. The EM algorithm (Shamshad et al., 2005) is applied to calculate the conditional probability (or the transition probabilities) of the net load, $Prob(L_{t+1}|L_t)$, for each hour in a day. In order to avoid over-training, the data is divided into a training set and a test set. Specifically, the first 20000 samples are used to fit the model, while the remaining 17583 samples are used as the testing set to
evaluate the performance of the proposed dispatch method.

### 7.5.2 General model characterization

A hybrid wind-diesel power system is considered with a diesel power capacity of 120 kW, a wind turbine output capacity of 110 kW, and an available storage capacity of 200 kWh (i.e., able to cover the energy demand for several hours). The full capacity range of the diesel unit, the wind turbine and the storage are assumed to be available for use. The diesel power capacity is discretized into 31 blocks, thus, the range of the discretized diesel power output goes from 0 kW to 120 kW at 4 kW steps. The wind power capacity and the storage capacity are discretized into 56 and 101 blocks, respectively, in a similar manner.

A Caterpillar Model D125-6 three-phase diesel genset (60 Hz, 1800 rpm, 480 Volts) is considered. This genset provides a power output of 125 ekW (156 kVA) in standby mode, and 114 ekW (143 kVA) in prime mode. The fuel consumption is 9.1 gal/hour at 100% load, 7.2 gal/hour at 75% load and 5.3 gal/hour at 50% load. The idling fuel consumption of the diesel genset, $C_r$, is calculated as 1.5 gal/hour, and the incremental fuel consumption for generating an additional unit of power, $C_i$, equals 0.0633 gal/kW.

According to (Zeljković and Rajaković, 2012), the fuel consumed for switching the diesel power generator on and connecting it to the grid is calculated as the equivalent of running the diesel engine at full power for several minutes. The switching cost equivalent to a three-minute full power fuel consumption, in units of fuel, equals 0.455 gal. The amount of power required for grid control and regulation in the storage-only mode, $b$, is 2 kW.

Recently, the implementation of distributive community energy storage systems has been widely discussed. According to (Zhu et al., 2012), the power capacity for a Lithium-
ion storage unit could range from 25 kW to 75 kW, with an energy capacity from 25 kWh to 75 kWh, and a round-trip AC energy efficiency of more than 85%.

In this case study, we consider an energy storage system with a capacity of 200 kWh and a maximum power output of 120 kW (equivalent to a couple of Lithium-ion units), with a round-trip energy efficiency, $\eta$, of 80%.

The proposed method is numerically solved using a backward recursive dynamic programming approach. Optimizing the dispatch of the isolated wind-diesel system throughout its entire life in a single shot is not computationally viable. A rolling-horizon approach is used instead, whereby the dispatch policy is computed over time windows of length $H$ and is updated every time new information about the net load is available. More specifically, the dispatch policy of the diesel genset is recalculated every 24 hours, when a new net load prediction is assumed to be issued.

On the other hand, by limiting the optimization of the system dispatch to windows of $H$ length, the rolling-horizon approach neglects the potential future value of the energy that remains on the battery at the end of every optimization window. This may jeopardize the optimality of the dispatch policy given by the rolling-horizon approach and is usually referred to as the effect of the terminal condition. An easy way to mitigate this effect is to sufficiently extend the length $H$ of the optimization window, so that the dispatch decisions to be made in the beginning of the scheduling horizon are unaffected.

Table 7.10 shows the total system operating cost for different lengths $H$ of the optimization window. The test set is divided into five equally distributed subsets with 3000 sample each. Results show that the terminal effect can be suppressed if the optimization
window spans more than 72 hours. In this study, the length of the optimization window is set to 96 hours.

<table>
<thead>
<tr>
<th>Length of the optimization window (hour)</th>
<th>24</th>
<th>48</th>
<th>72</th>
<th>96</th>
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</thead>
<tbody>
<tr>
<td>Subset 1 (3000 samples)</td>
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<td>11384.1</td>
<td>11380.9</td>
<td>11380.9</td>
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<tr>
<td>Subset 2 (3000 samples)</td>
<td>10511.7</td>
<td>10318.0</td>
<td>10318.0</td>
<td>10318.0</td>
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<tr>
<td>Subset 3 (3000 samples)</td>
<td>9176.4</td>
<td>8976.5</td>
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<td>Subset 4 (3000 samples)</td>
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<td>11169.5</td>
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<tr>
<td>Subset 5 (3000 samples)</td>
<td>11200.6</td>
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<td>10957.9</td>
<td>10957.3</td>
</tr>
<tr>
<td>Test set (17583 samples)</td>
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<td>62222.6</td>
<td>62217.3</td>
<td>62217.3</td>
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</tbody>
</table>

Table 7.10: Total operational cost (in equivalent gallon) for different optimization window length H.

The proposed model is programmed using Matlab and the optimization is carried out on a personal computer (AMD Athlon 5200+, 2 GB RAM, Microsoft Windows XP). The computational time required for each day-ahead scheduling period is about 30 minutes.

### 7.5.3 Optimal dispatching scheme

Figure 7.3 and Figure 7.4 show the optimal dispatch of the diesel generator under the example daily load profile, calculated by the proposed method, at Time 7 (7am) of the 24-hour rolling horizon scheme, as an example. The optimal diesel power output depends on the energy level in the storage, the net load, and the working status of the diesel engine in the previous time period. In these figures, the amount of energy available in the storage at Time 7 is indicated on the X-axis, and the net load level on the Y-axis. The grey-map in these figures indicates the optimal diesel power output.

In Figure 7.3, it is assumed that the diesel engine is shut off during Time 6. It can be observed that in Time 7, if there is a positive net load and the energy stored is not enough to fully supply it, the diesel engine should be restarted and the power output should
be set high and save the extra diesel energy in the battery. Thus, the system can benefit from the higher diesel efficiency that characterizes higher levels of diesel power output. On the contrary, when the energy stored is sufficient to cover the positive net load, it is optimal to just use the energy from the battery and keep the diesel engine offline.

If there is a negative net load, the optimal dispatch decision varies. Since the excess wind power can be stored (and used in the future) when the diesel engine is running, it is optimal to restart the diesel engine when the energy level in the storage is low or the
potential excess wind power is high. In general, the less the energy available in the storage and the less the energy available from the wind, the higher the optimal diesel power output. If the energy level in the storage is high, the optimal strategy tends to use the stored energy.

At the same time, the comparison of Figures 7.3 and 7.4 reveals that the optimal dispatch strategy is strongly affected by the on/off state of the diesel engine in the previous time period. Indeed, the inked area in the case of a spinning diesel engine is clearly larger than the inked area when the diesel engine is previously shut off. This shows that the
optimal on/off state of the diesel genset tends to remain the same as that of the previous
time period unless the expected benefit of changing this state could cover the switching
cost.

The optimal dispatch strategy is also highly influenced by the net load profile.
Figure 7.5 shows the optimal diesel dispatch policy at four different time periods (Time
4, 10, 16, and 17). The difference between these dispatch policies indicates that the pro-
posed method adapts dynamically to the daily net load pattern as well as to the net load
uncertainty.

For example, at Time 4 (4am), if the battery is not fully charged, the optimal
dispatch policy suggests charging the battery as much as possible (by keeping a low diesel
power output to regulate the power grid and storing the excess wind power, which corre-
sponds to the light-grey area in the grey-map). However, at Time 16 (4pm) and 17 (5pm),
the battery should be charged only if it is almost fully depleted. The difference in the charg-
ing strategy of the battery between the early-morning and the afternoon can be explained
as an effective way to take advantage of the load shifting capacity provided by the energy
storage device.

Despite the fact that the net load at Times 16 and 17 is quite similar, the corre-
sponding optimal dispatch strategies are slightly different, because the future expectation of
the net load at Time 17 is higher than Time 16. As a result, the optimal dispatch decision
at Time 17 is more likely to keep the diesel engine spinning.
Figure 7.5: Optimal diesel power output at Time 4 (upper-left), Time 10 (upper-right), Time 16 (bottom-left), and Time 17 (bottom-right), given that the diesel engine is turned on during the previous time period.

### 7.5.4 Out-of-Sample Case Study

In order to evaluate the performance of the proposed dispatch method, an empirical 7-day (168 hours) simulation study is conducted. The predicted load profile for each day is shown in Table 7.11. The prediction error is modeled using a Gaussian white noise, $N(0, 2)$ in kWh. Day-ahead dispatch strategies are generated each day before the operating period using the proposed method.

The resulting optimal dispatch policy is applied to the test dataset, which contains...
17,583 time series samples of wind power output data. An out-of-sample study is, therefore, conducted, since no information from the test dataset has been used to determine and calculate the proposed dispatch strategy. The test dataset is uniformly divided into 100 sub-sets with 170 hourly time-series data (the last 583 data are disregarded). Then, the 7-day real-time operation simulation is tested individually using these 100 sub-sets (since a 7-day simulation needs 168 hourly data, the last two data in each sub-set are disregarded).

Technical limitations should be considered in the model. According to the National Renewable Energy Laboratory (Drouilhet and Shirazi, 2002b), it is not recommended for diesel power generators to be used under its minimum allowed loading. The experience in Wales indicates that the minimum load is 20-25% of the rated capacity of the diesel engine (Drouilhet and Shirazi, 2002b). Thus, in this case study, we keep the diesel power generator from working under its 25% capacity. This can be easily achieved in the proposed dispatch method by disabling the working statuses with power output under the threshold capacity.

The predefined charging and discharging strategies proposed by (Barley and Winn, 1996) are considered as benchmarks. More specifically, we use the "Frugal discharge strategy" to control the discharge of the battery, because the battery wear cost is here assumed to be zero or very small. Therefore, it is more economical to stop the diesel engine and use

<table>
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<td>25</td>
<td>35</td>
<td>25</td>
</tr>
</tbody>
</table>

Table 7.11: Day-ahead load prediction (kW) in the 7-day simulation.
the battery instead "to meet the net load whenever there is enough stored energy (Barley and Winn, 1996)."

Furthermore, we consider two different charging strategies, namely: i) the “Load following strategy”, where the diesel power output is set to match the net load, and the battery is never charged with diesel power; and ii), the “Full power strategy”, according to which the diesel engine is always running at the rated capacity, and the battery is charged using both wind power and excess diesel power. Also we establish the set-point of this dispatch strategy at 80% of the state-of-charge (SOC) of the battery, which implies that if the SOC goes above 80%, the discharge of the battery is prioritized in the next time period to utilize the battery power and thus prevent overcharging.

Figure 7.6 shows the operation of the hybrid wind-diesel power system according to our proposed dispatch method (top), the “Full power strategy” (middle), and the “Load following strategy” (bottom). To quantitatively assess the performance of the proposed dispatch strategy, Table 7.12 compares the average fuel consumption and the standard deviation of operating the hybrid wind-diesel system under the different dispatch strategies through the 100 sub-sets.

The proposed dispatch strategy consumes less diesel fuel than the two benchmark strategies in 100% (100 out of 100) of the sub-test-sets. The average fuel saving rate (defined as one minus the fuel consumption under the proposed strategy over those under the benchmark strategies) is 8.6% and 6.0%, compared to the “Load following strategy” and the “Full power strategy”, respectively.

The difference in performance can be explained as follows. The “Load following
strategy” does not optimize the diesel output efficiency. Since it “follows” the net load, the diesel engine is more likely to work in the range of low power outputs, resulting in a higher generation cost on average. In the “Full power strategy”, the diesel engine always works at the rated capacity, where the average generation cost is the lowest. However, the on/off status of the diesel unit is consequently forced to change very frequently, see Figure 7.6.

As a result, the total cost is substantially reduced by the proposed dispatch method, as reported in Table 7.12. This is so because our optimization framework simultaneously account for the diesel engine efficiency, the expected net load profile, the energy storage state, and the potential switching cost to determine the dispatch decision.
154

<table>
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<tr>
<th>Fuel consumption in gal</th>
<th>Average</th>
<th>STD</th>
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<tr>
<td>Proposed method</td>
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<tr>
<td>Load following strategy</td>
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<td>145.61</td>
</tr>
<tr>
<td>Full power strategy</td>
<td>580.54</td>
<td>142.98</td>
</tr>
</tbody>
</table>

Table 7.12: Total fuel consumption (in \textit{gal}) of the dispatch realization of the 100 sub-set data.

7.6 Discussions

In this section, several practical issues that may arise when applying the proposed method to operate an isolated hybrid wind-diesel power system are discussed.

7.6.1 Battery Wear Cost

Next, it is explained how cost function (7.9) can be generalized to include the battery wear cost and investigate the impact of this cost on the operation of the hybrid wind-diesel power system. In this example, the battery wear cost is considered in the phase when the battery is charged. An additional term corresponding to the battery wear cost is added to equation (7.9). Specifically, when the diesel power output is higher than the net load, the difference between the diesel power and the net load, \((P_t - L_t)\), is used to charge the battery. Considering the round-trip efficiency, the energy that can be utilized in the charge-discharge cycle is \(\eta \times (P_t - L_t)\). Thus, the battery cost in this cycle equals \(C_{bw} \times \eta \times (P_t - L_t)\), where \(C_{bw}\) is the battery wear cost. In the other cases, when the battery is discharging, no battery cost is considered. The cost function including the battery wear cost writes as follows,
According to (Chen et al., 2009), the wear cost for a Li-ion battery ranges from $0.15 to $1/kWh.cycle, and $0.05 to $0.8/kWh.cycle for a ZnBr battery. Considering that the average cost of diesel fuel during 2014 was $4/gallon, the cost for running the diesel power generator at the rated capacity can be roughly estimated at $36.4/hour. The diesel power generator operates with maximum efficiency at the rated capacity. In this situation, the average cost for generating one kWh energy amounts to $0.303/kWh.

Figure 7.7 shows the operation of the hybrid wind-diesel power system according to the proposed dispatch method under three different values for the battery wear cost, the time dimension (in Hour) is indicated on the X-axis, and the system dispatch status on the Y-axis. It turns out that the system dispatch policy resulting from the proposed dynamic programing model becomes more similar to the Load Following strategy as the battery wear cost is increased.

The proposed dispatch method performs the best in terms of total system operating costs. The total cost associated with the Full Power Strategy grows rapidly with the battery wear cost, because it makes an extensive use of the battery. The proposed dispatch method also performs better than the Load Following strategy, because it simultaneously minimizes all sources of costs, i.e., the fuel consumption expenses, the switching cost, and the battery wear cost. Table 7.13 provides the detailed breakdown of the system operating costs under different battery wear cost levels. The test set with 17583 samples and the daily load profile
7.6.2 Load Fluctuations

Load fluctuations are clearly a great challenge for power systems in general and especially, for a small-scale isolated wind-diesel power system.

One way to efficiently deal with load fluctuations is to increase the time resolution of the proposed stochastic dynamic programming model, for instance, by considering 15-min time steps instead of hourly intervals. In general, the use of a finer time resolution would previously described are used.
allow capturing, more accurately both the cost of the variability of wind and demand and the benefits brought in by the flexibility provided by the diesel power generator and the electricity storage. This, of course, would come at the cost of increasing the computational burden of the proposed model. In this work, hourly time steps have been considered as a good compromise between model accuracy and tractability, following the example set in many other studies and applications (see, e.g., (Deane et al., 2014)).

On the other hand, if finer time resolutions are to be considered, the assumption that wind power production can be adequately modeled as first-order Markov chain (proposed in (Shamshad et al., 2005)) may no longer be valid (Brokish and Kirtley, 2009). As stated in (Hayes and Djokic, 2013), more advanced models for wind power production should be used in practical applications involving time steps shorter than one hour. Therefore, a potential avenue for future research is to adapt the proposed system dispatch method for real-time operation, by using it in combination with advanced techniques for

<table>
<thead>
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<tr>
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<td>33590</td>
<td>37323</td>
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</table>

Table 7.13: Total fuel consumption and battery wear cost (in equivalent gallon) of the dispatch realization under different battery wear levels.
very short-term wind power forecasting.

Finally, the impact of unexpected load fluctuations on the performance of the proposed dispatch method is analyzed. For this purpose, it is assumed that the prediction of the net load is unbiased, meaning that the sum of the plausible intra-hourly net load deviations is zero. Then, two cases should be distinguished and discussed:

1. The diesel unit is on. In this situation, the dispatch decision given by the proposed model is still optimal, because the net load fluctuations do not entail any extra cost to the system due to the linear nature of the fuel-consumption function. Indeed, denote the average net power consumption in the hourly dispatch period $t$ by $L_{t}^{ave}$ and the corresponding optimized diesel power output by $P_{t}^{s}$. Now let $\Delta(\tau)$ represent the net load deviation with $t=\tau=t+1$. The actual net power consumption at time instant $t$ is, therefore, $L_{t}^{ave} + \Delta(\tau)$, which is accommodated by changing the diesel power output from $P_{t}^{s}$ to $P_{t}^{s} + \Delta(\tau)$. Since the predicted power net load is unbiased, the following equation holds, $\int_{t}^{t+1} (L_{t}^{ave} + \Delta(\tau)) d\tau = L_{t}^{ave}$, because $\int_{t}^{t+1} \Delta(\tau) d\tau = 0$, which leads to an hourly diesel fuel consumption equal to that estimated by the proposed dispatch method: $F = \int_{t}^{t+1} (F_{0} + F_{i} \times (P_{t}^{s} + \Delta(\tau))) d\tau = F_{0} + F_{i} \times P_{t}^{s}$.

2. The diesel unit is off. In this case, the electricity load is supplied by the wind power unit and the battery. Since the wind power unit is non-dispatchable, the battery must cover the unexpected load fluctuations. An easy way to guarantee that there is enough energy in the battery to this end is to impose a lower bound on the battery energy content below which the battery cannot be drained. To illustrate this point, the simulation conducted in Section 5.1 has been repeated, this time, however, imposing an energy reserve
margin of 10 kWh in the battery (to deal with intra-hourly load fluctuations, if needed). Results show that keeping this reserve margin available in the battery increases fuel diesel consumption in 136 gallons (from 62217 gallon to 62353 gallon). The cost of this extra fuel consumption should be understood as the cost of keeping some battery capacity ready to be used on request during the intra-hour operation of the isolated wind-diesel power system.

7.6.3 Controllable Load Response

Demand response has been identified as a potential valuable option to enhance the operation and efficiency of isolated power systems (Dietrich et al., 2012). To illustrate the potential benefits of demand response within the proposed dispatch approach, a new simulation has been conducted in which an interruptible load of 5 kW is considered. It is assumed that the load can be fully interrupted on the request of the system operator at a cost (partial interruptions are not considered for the sake of simplicity). Two different values are proposed as the interruption cost, namely, $2/hour and $0.8/hour. With the introduction of the interruptible load, the proposed dispatch method must now decide the on/off status of the diesel genset, its power output, and whether the interruptible load is to be curtailed or not. Table 7.14 provides the breakdown of the system operating costs under the two different values of the interruption cost. Systems costs are given in terms of diesel fuel consumption in gallons (fuel price is set to $4/gallon).

As expected, fuel consumption is reduced when the interruptible load is introduced. Furthermore, cost savings are larger when the interruption cost is lower.

This section is concluded by pointing out that the consideration of interruptible loads increases the computational complexity of the proposed dynamic programming so-
Table 7.14: Total system operational cost (in equivalent gallon) under different values of the interruption cost.

<table>
<thead>
<tr>
<th></th>
<th>No dispatchable load</th>
<th>With dispatchable load</th>
<th>Cost at $2</th>
<th>Cost at $0.8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total cost</td>
<td>62217</td>
<td>62185</td>
<td>60272</td>
<td></td>
</tr>
<tr>
<td>Fuel consumption</td>
<td>60970</td>
<td>60892</td>
<td>56134</td>
<td></td>
</tr>
<tr>
<td>Switching cost</td>
<td>1248</td>
<td>1219</td>
<td>1265</td>
<td></td>
</tr>
<tr>
<td>Load shifting cost</td>
<td>0</td>
<td>73</td>
<td>2873</td>
<td></td>
</tr>
</tbody>
</table>

7.7 Conclusion

In this chapter, a stochastic dynamic programming model is applied to optimize the diesel dispatch operation of hybrid wind-diesel power generating systems. The method determines the optimal diesel power output depending on the current net load, the energy storage status, the cost function of the diesel genset, and the previous operational actions. The optimal dispatch decision is determined according to the value (operating cost) in the current time period plus the expected conditional operating cost that this decision may entail in the future given the probable outcomes of the uncertain wind power production (treated as a negative load). Results show that the proposed dynamic method has a general better performance than the existing pre-defined dispatch strategies for practical implementations.

The proposed method has great potential for practical use given that proper cost structures are considered and uncertainty modeling is properly handled. Despite the fact that the numerical study includes a relative simple diesel engine cost function and wind
power model, this dynamic programming framework can be adapted to multiple diesel engines and more complex models for the wind power uncertainty in a straightforward manner. Further research could aim at combining the proposed dynamic programming framework with both short-term wind and electricity load forecasting.
Chapter 8

Conclusions and future work

In this chapter, we summarize this dissertation by presenting the main conclusions. We also discuss the potential research topics and future studies based on this work.

8.1 Conclusions

Due to the environmental advantages when compared with the traditional diesel-only power plants, hybrid wind-diesel systems have shown their great potential in providing energy supply in remote and isolated areas. The integration of wind turbines reduces the diesel consumption in the local communities, and thereby the greenhouse gas emission and pollution caused by the combustion and transportation of diesel fuel. Recent research shows that a sustained growth of wind power penetration may be expected in both existing and future isolated hybrid grids.

Since wind energy is unstable and uncertain, its introduction into the traditional power grid with controllable energy plants may create new challenges for power producers
and operators. After analyzing the performance and statistics of some currently implemented hybrid systems, the challenges can be summarized as follows:

- On the one hand, the volatility of wind power causes uncertain system performance and, correspondingly, the financial and environmental benefit. Therefore, a novel quantitative model is necessary to take into account this new source of risk in the project planning and value assessment phase.

- On the other hand, the integration of wind power requires additional reserve and spinning power to cope with the power imbalance and unpredictable power change. Especially in the case of hybrid wind-diesel power systems, the additional/supplementary requirement of reserve and spinning power from the diesel engines significantly decreases the diesel efficiency. Advanced power scheduling and dispatching methods should be developed to allocate the reserve power and optimize the dispatch scheme.

Deterministic methods and models are not sufficient to simulate the impact of uncertainty, since power producers may choose different operational actions in response to it. Therefore, the operational flexibility of the power system has to be modeled first. Then an optimal decision making method has to be developed to optimally adapt the operational actions to the unpredictable power imbalance caused by wind power fluctuations.

The real option theory, implemented as a multi-stage decision optimization, provides the framework to solve the problem in a path-dependent, dynamic and adaptive approach. We show that through passive managerial actions, the risk distribution can be controlled and managed, and quantitative methods are introduced and discussed. We show that the conditional expectation of the future outcome under certain decisions has a signif-
ificant influence when selecting the optimal decisions. To model the conditional value, the regression based method, scenario simulations, and probability theory are normally applied. Among them, we focus on the Markov decision model with probability theory for solving the decision process.

In this dissertation, optimization and value assessment methods are investigated, developed and implemented with practical case studies and numerical simulations.

Firstly, in a case study focusing on the San Cristobal wind-diesel project, we demonstrate that uncertainties, such as wind uncertainty and operational uncertainty, are important factors affecting the performance of such systems. Dispatch strategies taking into account the energy storage component should be correctly simulated in the feasibility studies and in practical operations to improve the diesel efficiency.

In the next step, we simulate a hybrid wind-diesel power plant using the real option theory to analyze the impact of flexible operational actions on the project cash flow. Switching options of wind turbines are defined to model the operational strategies. The simulation proved that the total expected value of the hybrid power plant can be increased as a consequence of the optimal operational policy.

The result of the numerical case study also shows that the cash flow of a hybrid system is significantly impacted by the wind source distribution. The limitation of demand and local wind power abundance are the main factors that impact on the optimal scale of the hybrid project.

And for more practical applications, a short term diesel dispatching model is designed to improve the diesel efficiency for a hybrid plant while maintaining the system
stability and security. Because of the free-cost nature of the wind energy, the operator of a hybrid wind-diesel power plant seeks to maximize the diesel displacement in order to maximize the global profit.

The diesel engine reaches its maximum efficiency at the rated capacity. Therefore, in order to increase the expected diesel efficiency, we apply a dynamic programming method, which has the following features:

- The optimal diesel engine working status can be determined under each given condition, with the lowest expected future diesel consumption.
- The optimal strategy depends on the current system status, including the wind power, current diesel power output, and current storage level.
- The operational strategy is generated considering the possible scenarios of future uncertainty.
- The optimal decision is made according to the cash flow under the chosen action during the current time period plus the expected conditional values that this decision will have in the future, which is modeled as the net load. The optimal decision is made according to the value caused by the action on the current time period plus the expected conditional values that this decision will have in the future.

To summarize, this dissertation answers the research question proposed in the introduction.

The results of the presented studies confirms that the performance and profitability of a hybrid wind-diesel power plant are significantly affected by uncertainty. In order to
make optimal decisions, power plant operators and managers should not just focus on the
direct outcome of each operational action; neither should they make deterministic decisions.
The correct way is to dynamically manage the power system by taking into consideration
the conditional future value in each option in response to the uncertainty.

8.2 Future research

Future research on different aspects can be conducted to improve or complement
the proposed method to achieve further and more comprehensive knowledge of the hybrid
renewable systems, we list some possible future tracks for research, as follows:

1. When applying the presented model to a specific system configuration, technical
issues such as the rambling effects, reserve power, imposed current and other limitations
should be considered.

2. The switching costs are discussed empirically in this dissertation. Detailed
calibration and assessment of the cost functions for each component is necessary when
implementing the proposed method in a real project. The most important factors and costs
in the model includes the equivalent cost for start-up and shut-down of each component,
the equivalent cost in charging and discharging the battery, and the cost function for the
diesel engine.

3. Other renewable energy sources and technics have been tested and developed
continuously, such as the solar power and hydro power, while some of them are more reliable
and are complementary to wind power, such as the pumped hydro plant. When assessing
the project value or optimizing the decision process, additional energy sources should be
considered.

4. This dissertation focuses on an isolated power grid, in which no external energy supply is considered. Since many remote communities are supplied with existing power grids with a limited power connection. It could be of interest to focus research on simulating the impact of wind energy in such power systems.

5. For a hybrid power plant, the wind power fluctuation and the energy demand load are the basic sources of uncertainty. The following aspects may be considered as potential future developments regarding the forecasting and modeling of uncertainty.

- Probability forecasting tools for short term power load are necessary.
- Long term wind and power load forecasting should be considered.
- Additional simulation of special events such as system failure, or wind turbine availability forecasting may be integrated into the model.

6. Further research could be carried out by extending this model to higher orders of Markov decision process, in order to adapt uncertain variables which exhibit a high order time dependency.

7. A risk analysis can be performed when analyzing the conditional distribution. Other than maximizing the expected profit, a further risk management tool would control the risk distribution in each time step.

Finally, The proposed diesel dispatch model can be also extended and applied to the optimization of other wind power systems. For example, to optimize the power dispatch and bidding strategy of a power producer in the pool-based electricity market.
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