DOCTORAL THESIS FOR THE DEGREE OF PHILOSOPHIAE DOCTOR

HYBRID RENEWABLE POWER SYSTEMS FOR THE MINING INDUSTRY: SYSTEM COSTS, RELIABILITY COSTS, AND PORTFOLIO COST RISKS

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DECLARATION

I, Joël Jérémie Samuel Guilbaud, declare that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

London, June 2016

Joël J.S. Guilbaud

We have reached a new milestone as a human family. With seven billion of us now inhabiting our planet, it is time to ask some fundamental questions. How can we provide a dignified life for ourselves and future generations while preserving and protecting the global commons - the atmosphere, the oceans and the ecosystems that support us?

Ban Ki-moon

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PUBLICATIONS

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ABSTRACT

The mineral sector is responsible for more than 38% of total industrial energy use and 11% of total final energy consumption. A rising trend in the industry is the search for cleaner, less carbon-intensive and more efficient energy technologies that can also bring new business opportunities to the industry. Evidence suggests that the inclusion of energy storage and renewables alongside traditional fuel-based power alternatives can both reduce generation costs and carbon emissions in off-grid and distributed power systems. Previous research has quantified this outcome for other industrial and domestic sectors but little investigation has taken place to characterise the potential of hybrid systems in mining settings.

The interest of this research is to assess the economic potential of hybrid renewable systems and evaluate the trade-offs associated with the context-dependent factors of the mining industry. An energy optimisation model, named HELiOS-Mining, was developed in order to account for these factors, and search for the least-cost generation alternatives in relation to technical characteristics (i.e. storage strategies, dispatch, demand-shifting, reliability requirements, fuel-mix), economic specificities (i.e. value of lost load, portfolio cost risk, financing), and spatial factors (i.e. access to resources, climate). Three major mining regions are investigated, including: grid-connected and off-grid mining in Northern Chile as well as off-grid mining in North-Western Australia and Yukon, Canada.

The results of this research allow important insights to be made into the economics of hybridised power systems in mining settings. Research findings have identified that hybrid renewable power systems can generate life-cycle cost savings of up to 57% and carbon savings of up to 82% (against diesel or grid power baselines). Power systems that feature a renewable penetration of 60 to 85% of total capacity have the lowest costs in three out of four selected mines. Furthermore, portfolio analysis has demonstrated that such power systems can help reducing the cost risk of the industry associated with fuel price variations and carbon policies. Results also illustrate how assumptions about risk factors can drive large shifts in optima, and that concentrated solar power could be a key enabling technology for reducing the emissions of the mining industry.

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INTRODUCTION

1.1 MOTIVATION FOR THIS THESIS

The mineral sector is responsible for more than 38% of total industrial energy use and 11% of total final energy consumption (McLellan et al., 2012). This energy consumption is set to double by 2050 compared to 2009 standards if no policy measures are taken (UNIDO, 2010). At the same time, the mining sector is coming under significant pressure to decrease the amount of energy consumed and greenhouse gases emitted (Norgate and Haque, 2010). According to the fifth report of the carbon disclosure project, the main trend in the industry is the search for cleaner, less carbon-intensive and more efficient technologies, that can also become new business opportunities to the industry.

Whereas it is technically feasible for mining companies to power their operations with hybrid renewable energy systems, it is unclear whether these technologies can deliver economic benefits to the industry. Compared with fossil fuels, renewable energies suffer from a number of technical and economical disadvantages such as intermittent supply and higher capital costs. However, energy storage technologies can act as technological enablers, and, in certain conditions, can successfully help renewable technologies to meet power demand and provide a reasonable return on investment (Denholm et al., 2010). Together, renewable energy sources and energy storage might be able to replace or complement conventional energy sources of the mining industry. The tipping point being the achievement of grid parity in distributed systems and diesel/gas parity in stand-alone systems. (Breyer and Gerlach, 2013). That is, when the generation unit cost of hybrid renewable systems is equivalent to the electricity prices of conventional sources.

To date, there is little research available to assess the economic value of these systems for mining activities. Previous scientific studies are limited to isolated systems (Weisser and

Garcia, 2005; Abbey et al., 2008) or country-scale systems (Wilson et al., 2010; Ibrahim et al., 2011; Korpaas et al., 2003), but no studies have done similar investigations for mining settings. Past studies for mining are limited to scoping (Paraszczak and Fytas, 2012), energy guidelines (Azapagic, 2004; Hilson and Murck, 2000), and global potential (McLellan et al., 2012). Whilst these past studies have provided initial estimates for alternative energy sources, their results do not account for the context-dependent elements of the mining industry. Alternatively, a number of studies have been published by consulting companies and public organisations, but there is a lack of clarity in reporting technical and economic assumptions, and often little consideration for uncertainty, which produced a widely diverse set of results (Branker et al., 2011). These different degrees of methodological completeness and the use of similar assumptions for different technologies could result in both sub-optimal decisions and missed opportunities for carbon savings. It has therefore become critical to provide a robust economic assessment of these technologies to the industry and its stakeholders.

In the mining sector, the economic assessment of hybrid renewable systems is dependent upon complex relationships between non-linear costs, geographical attributes, uncertainty parameters, financing mechanisms, and energy demand (Rabiee et al., 2013). For instance, in contrast to diesel and gas fired generators for which reliability is generally well known, hybrid renewable systems require extensive analysis for understanding both uncertainty factors and system integration. These systems also face problems over amortization. Mining time-frames are not always compatible with the lifetime required to recover the investment. Financing these systems brings additional challenges associated with risk and uncertainty over cash flows, especially for the newest technologies. Many hybrid power systems are also competing against the construction of new transmission lines, which may encompass high capital costs for building roads, substations and other infrastructures. Ultimately, the challenge lies in understanding the economic trade-offs associated with numerous exogenous and endogenous parameters.

In this context, the interest of this research is to assess the economic potential of hybrid renewable systems and evaluate the trade-offs associated with the context-dependent factors of the mining industry. It is thus proposed to construct an economic model that accounts for these parameters, and searches for the least-cost options in relation to technical characteristics (i.e. load curves, demand-shifting of mining processes, reliability requirements, energy mix), economic specificities (i.e. value of lost load, cost risk, financing mechanisms), and spatial factors (i.e. access to resources, climate). As a result, the findings could help increasing the uptake of hybrid renewable systems in mining and therefore help reducing the emissions of the industry.

1.2 RESEARCH QUESTIONS AND LAYOUT OF THE THESIS

On the basis of the research gaps that have been identified in the literature review of this thesis in chapter 2 on page 17, the following research questions are tackled in this PhD research:

1. **To what extent can hybrid renewable power systems minimise electricity costs and reduce carbon emissions of the mining industry?**
2. **What is the optimal trade-off between capacity cost and reliability cost?**
3. **What is the influence of cost risks on the economics of such power systems?**

Chapter 3 on page 45 details the methods that have been chosen to answer these research questions whereas chapter 4 on page 91 provides the key data sources and parameters that were applied to perform the research.

Once the context, literature, methodology, and parameters have been presented, the results are provided in the three following chapters. Chapter 5 on page 109 addresses the first research question on system costs. Chapter 6 on page 163 focuses on the second research question associated with reliability costs. Chapter 7 on page 181 addresses the portfolio costs and provides the results of a decision-analysis with respect to different risk factors.

Research limitations and key areas of uncertainty are provided in chapter 8 on page 213 along with a discussion on generalisation. Finally, the conclusion chapter 9 on page 229 summarises the key findings and main areas of research contribution.

A presentation of the key energy characteristics and challenges of the mining industry is provided as follows.

1.3 CONTEXT

1.3.1 *Background on the mining industry*

1.3.1.1 *Overview*

In the current global economy, the mining sector is relatively small in terms of the world's workforce - 30 million people are involved in large-scale mining and an additional 13 million in small-scale mining, excluding mineral fuels (Azapagic, 2004). Despite the small workforce involved in mining, the industry is responsible for more than 38% of the total industrial energy use, 15% of the total electricity usage, and 11% of the total final energy consumption. This translates into the consumption of 19% of coal and coal products, 5% of all gas products, and 2% of the global oil supply (McLellan et al., 2012).

Mining activities can be classified within three major categories: metallic minerals, non-metallic minerals, and mineral fuels.

- Metallic minerals: Include minerals that can be melted to obtain new products. It includes ferrous metals (iron, manganese, molybdenum, and tungsten), non-ferrous metals (metals that do not contain iron in appreciable amounts such as copper, aluminium, titanium, lead, zinc, and nickel), precious metals (gold, silver, platinum), and the radioactive minerals (uranium, thorium, and radium);
- Non-metallic minerals: Minerals that do not yield any product on melting. This category includes phosphate, potash, halite, trona, gravel, limestone, sulphur and many others;
- Fossil fuels or mineral fuels: Include the organic mineral substances that can be used as fuels in order to produce energy. They are composed of coal, petroleum, natural gas, methane, gilsonite, and tar sands.

Metallic minerals are mined from both open pits and underground, whereas non-metallic minerals are most often extracted through quarrying. Metals are used in a number of applications such as electronic, electrical, or automotive. Non-metallic minerals are used in a wide range of industries, from the construction industry (i.e. cement, bricks, and glass products) to consumer goods (i.e. tableware, ceramics). Markets for non-metallic minerals are often restricted to local supplies due to transportation costs and resource availability. Conversely, the metallic mineral industry is traded globally - e.g. London Metal Exchange, New York Commodity Exchange. It is characterised by high levels of competition, moderate barriers to entry (i.e. high sunk costs but low intellectual property), homogeneous products, rational buyers (i.e. commodity exchanges), and profit maximisation (Azapagic, 2004). Over the last decades, the price of commodities has widely fluctuated in relation to market demand, production costs (as shown for copper in figure 1.1) - largely associated with ore grade and energy prices as well as mineral availability, and technological improvements (Starke, 2002). For instance, technological breakthroughs in the late 19th and early 20th centuries helped mining companies to increase efficiency, lower prices, and generate higher profits (e.g. cheap electricity enabled the smelting of aluminium).

Figure 1.1: Historical price fluctuation for refined copper (Nasdaq, 2016)

Whereas these different mining sectors share similar characteristics, they differ on numerous points. For instance, one key characteristic of mineral fuel is the depletion of resource over time. On the contrary, other minerals have a much lower depletion rate, as they can be recycled and reused for new fabricated products. Yet, the sustainability issues are shared by all mineral sectors. In this thesis, the focus is on non-ferrous minerals - because of process similarities, high electricity demand, and remote locations. However, it is worth pointing out that the key energy issues discussed in this thesis are potentially applicable to other minerals (as discussed in section 6.5 on page 180).

1.3.1.2 *The non-ferrous metal industry*

The non-ferrous metal industry consists of metals that do not contain iron in appreciable amount. The production of non-ferrous metals consists of three major processes. In simple terms, the ore is extracted in the mining process, crushing and grinding - together constituting the milling process - produce a concentrate from the ore, and refined metal or alloy is produced in the smelting and refining processes (Barbour, 1994).

Even though some mining companies only produce concentrates, most are vertically integrated and take part in all phases of the mining process (Slade, 2004).

In addition, most mining companies produce several commodities. This is because many mines contain ores carrying more than one mineral. In addition, multimarket production help mining companies to develop common practices across commodity markets - therefore taking advantage of economies of scale, reducing commodity price risk, and increasing efficiency. Despite substantial economies of scale, mines of non-ferrous minerals are not geographically concentrated. Instead, they are globally distributed across various countries (Ibid).

On the production side, the similarities of various commodities across the non-ferrous metal industry can be summarised in four key aspects. First, they have a similar production process including mining, milling, smelting, and refining (Barbour, 1994) - as opposed to, for instance, non-metallic minerals which do not yield any product on melting. Second, their production processes imply a high demand for electricity at all time of the day and night - averaging more than 60% of the total energy consumption (UNIDO, 2010). Third, the geographical locations of major non-ferrous mines are often remotely located, often at sites with large renewable resources (e.g. high solar irradiation in copper mines of Chile, Zambia, and Australia), and sometimes have a limited or no connection to the mainstream electricity grid (Paraszczak and Fytas, 2012). Fourth, they are homogeneous commodities that are exchanged on global mineral markets (Slade, 2004).

On the consumption side, conversely, the diverse commodities of the non-ferrous metal sector are used in heterogeneous fabricated products. For instance, the largest use of copper is in electrical wire, while aluminium is used in food-packaging products (Emsley, 2011). This means that each mineral is exchanged in a distinct product market. Specifically, there are 8 non-ferrous commodities traded in 16 world markets (e.g. London Metal Exchange).

1.3.2 *Environmental and economic challenges*

1.3.2.1 *Sustainability issues*

Current practices of mining and mineral processing cause large environmental impacts, including air pollution, heavy metals contamination, gaseous emissions, soil contamination, and the destruction of vegetation and habitat (Hilson and Murck, 2000). Other adverse effects include the use of sizeable portions of land for stockpiling ore and significant alterations of surrounding landscapes for open-pit mining. Mining operations also require significant amounts of water, which can be a significant concern if the mine is located in an arid area. As a result, mining companies tend to develop vast pumping schemes in order to supply water to the mine - therefore further altering the landscape along the pumping path. Water recirculation and recycling are also popular practices in mining. Yet, these practices depend on a number of factors including the cost of water, and the pollution caused by waste water (Lagos and Mardones, 1999).

Another significant environmental impact of mining activities is the emission of large amounts of greenhouse gases. Final energy consumption and electricity generation are a major source of direct emissions or indirect emissions of carbon into the earth's atmosphere. Another typical type of emission is sulphur dioxide (SO_2). When it poses a serious environmental problem, sequestration can be applied by acid plants that produce sulphuric acid - which can be sold or used for treating oxide ore in hydrometallurgy (Watling, 2006). However, acid plants consume energy and further increase the overall energy consumption of the mine (Alvarado et al., 1999).

To date, most of the mining literature on sustainable development focuses on recycling, conservation of assets, energy efficiency initiatives, management, and pollutants. For instance, Norgate and Haque (2010) provided a lifecycle assessment of the greenhouse gas emissions and embodied energy for the various mining and processing operations. Abdelaziz et al. (2011) reviewed the various energy saving initiatives of the industrial sector for management, technologies, and policies. They argued that energy saving initiatives have been found economically viable in most processes, and a significant amount of energy and emission can be saved. Azapagic (2004) has developed a framework for sustainability indicators in order to enable performance assessment and cross-comparison that includes the use of fossil fuels and renewable energies as part of an overall energy indicator. Hilson and Murck (2000) have provided some guidelines for enhancing sustainability in the mining sector. They suggested that extending social responsibility to mining stakeholders, better management practices, and cleaner technologies can both increase performance and contribute to sustainable mining.

Despite the inclusion of renewable energies in sustainable frameworks and mining guidelines, very little attention has been paid to assess the actual potential of clean energy technologies for the mining sector. A few past studies have investigated this issue with regard to the global potential of renewables in mining, and renewable sources for remote mining applications. Specifically, McLellan et al. (2012) have evaluated the global potential of renewable energies - in terms of energy demand and carbon emissions - for the mining sector; and Paraszczak and Fytas (2012) have discussed the possibility of implementing renewable energy sources in remote mines in which there is limited or no connection to the mainstream electricity grid. These studies found that mining emissions could be substantially reduced by including renewable sources in the mix. Solar thermal and hydropower were flagged as high potential by these studies. Yet, no study to date has economically compared the different renewable generation alternatives that are currently available.

The mining industry is also characterised by the type of stakeholders involved in the sector, including local authorities, governments, NGOs, and shareholders. Some of these stakeholders have a great influence on the economic objectives and environmental policies of a mining company. For instance, shareholders have traditionally favoured short-term profits over sustainability while NGOs have worked towards developing sustainable mining practices. Yet, there is a recent trend for shareholders to show interest in socially responsible investments. This trend might influence the practices and technological choices of mining companies so that the societal cost can be restrained. Similarly, most governments have shown interest in sustainable mining in order to protect local communities and reduce mining emissions (Azapagic, 2004).

1.3.2.2 *Economic issues*

Profit maximisation and competitiveness of the mining sector are essential for the industry in order to generate employment and wealth. This leads to several micro-economic and macro-economic issues. On the micro-level, the company needs to operate efficiently by minimising operating and capital costs in order to generate profits. On the macro-scale, mining activities provide economic benefits at the local and national level: injection of foreign currencies, contribution to GDP, tax revenue, investment, and employment (Azapagic, 2004). However, because mining activities have a negative impact on the environment, there are also adverse effects such as the emission of greenhouse gases (Hilson and Murck, 2000). Traditionally, micro-economic issues have dominated corporate decisions with a focus on short-term returns, which is one of the reasons why mining companies mostly employ expense-intensive energy technologies (i.e. using fossil-fuels) rather than cleaner energy sources that tend to be capital-intensive (i.e. solar PV, wind turbines) (Breyer and Gerlach, 2013). This contrast between fuel-intensive and capital-intensive alternatives is carefully investigated in chapter 7 on page 181.

To reduce the societal cost of mining activities, various environmental policies have been suggested. In the recent decades, increasing focus has been given to two particular policy instruments: the Pigovian tax (i.e. carbon taxation), and various trading schemes that let actors buy or sell emission allowances in the market [1]. These instruments have different characteristics across countries and are sometimes hybridised with both Pigovian taxes and trading schemes (Bovenberg and Goulder, 2002). This, combined with increasing fuel prices, has, in some cases, led to the implementation of a small share of renewable energy in the mining sector (McLellan et al., 2012).

Other economic issues associated with the mining energy systems are the cost risk, and the reliability costs. That is, the price uncertainty associated with future energy prices (as wells as other risks), and the price that a company is willing to pay to avoid an energy outage. Whereas the cost risk can be a technological enabler for renewable energy sources, the reliability costs can hinder take-up. Both concepts and their applications to hybrid renewable systems are examined in chapter 6 on page 163 and 7 on page 181 respectively.

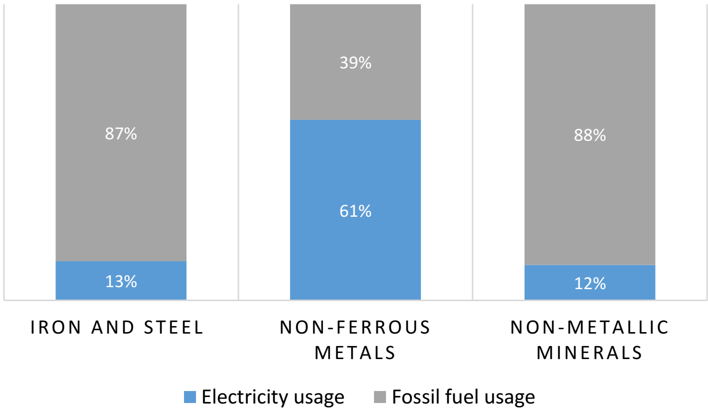
1.3.3 *Energy demand*

The mining sector, like other industrial sectors, is coming under significant pressure to decrease the amount of greenhouse gases emitted and energy consumed (Norgate and Haque, 2010). Yet, the energy mix and energy intensity differ widely according to the mineral type. For instance, the energy mix of the non-ferrous metals industry requires 61% of electricity - whereas it is only 13% for non-metallic minerals and 20% for iron and steel (McLellan et al., 2012). Furthermore, non-ferrous metals have a much higher energy intensity (GJ/t) than other minerals (see figure 1.2 and table 1.1). As a result, some mining sectors - such as the aluminium industry - have moved their operations to countries with lower energy prices. In particular, countries such as Iceland, Norway, and Canada have attracted new mining activities.

Another key issue of the mining industry is the increasing energy cost of drilling deeper as well as the problem of low grade ores. Recently, it was shown that metallic ore grades are globally falling because the reserves of higher ore grades have been progressively depleted. Past research has shown that the effect of lower ore grades on the environment is significant for ore grades below 1%, due to the fact that additional energy - and therefore emissions - is required to process the ore and treat the waste material. It was also argued that energy efficiency initiatives, carbon sequestration, and renewable energy sources are potential candidates to help mitigating this issue (Norgate and Jahanshahi,

[1] A review of relevant policy instrument is provided in section 8.3 on page 216.

Figure 1.2: Mix of the final energy consumption in the mining industry (McLellan et al., 2012)



2006; Norgate and Haque, 2010). Specifically, whereas energy efficiency initiatives would reduce the embodied energy of metal production, the use of renewable energy source would decrease the emissions of greenhouse gases. Ultimately, both approaches - as well as recycling current metals - are essential for improving the sustainability indicators of the mining industry. However, while the development of energy efficiency initiatives is an issue worth investigating, it is not within the scope of the current work.

Table 1.1: Summary of production, final energy usage, and energy intensity of the global mining industry (McLellan et al., 2012)

World data	Total energy GJ/t	Energy as electricity % of total	CO2 (tCO2/t)	CO2 from electricity % of total
Iron and Steel	18.80	13%	1.90	20%
Non-ferrous metals	60.00	61%	7.00	78%
Non-metallic minerals	3.30	12%	0.30	22%

ELECTRICAL ENERGY As shown before, the electricity usage in the production of non-ferrous metals contributes to 61% of total energy consumption and 78% of emissions of the sector (McLellan et al., 2012), and is therefore of high importance. If non-carbon electricity sources were to replace the current electricity sources, emissions would be reduced by approximately 7t of CO_2 per ton of final product. This carbon reduction could provide a significant marketing advantage for non-ferrous metals (e.g. aluminium) that are, because of their light weight, often considered for replacing steel products and thus providing further emission savings in transportation applications.

A number of mining processes are particularly electricity-intensive. The first mining phase requires electricity for shovels, drilling, lighting, and conveyor-belt. Second, the milling phase uses electricity for water-pumping, crushing, grinding, flotation, and smelting - especially flash smelter that uses significantly more electricity than older technologies. Finally, the last refining phase is based on electrolysis - either electrorefining or electrowinning - and requires large amount of electricity for purifying the metals (Davenport et al., 2002). Each of these major processes is composed of numerous sub-processes that typically run 24/7. Sub-processes that are potentially dispatchable (i.e. oxygen plant, air compression) could contribute to reduce the amount of energy storage required in hybrid renewable power systems.

Another key consideration associated with renewable electricity is the reliability of supply, both in terms of adequacy and security (Allan and Billinton, 2000). From an adequacy perspective, the inherent fluctuation of renewable electricity would be unacceptable and could potentially drive significant costs of outage. However, reliability issues can be mitigated by diverse energy storage technologies or other clean energy sources. Alternatively, diesel or gas generators - which are fully dispatchable - offer the possibility to deal with both intermittency and energy security issues (Huneke et al., 2012).

THERMAL ENERGY The thermal energy required for the production of non-ferrous metals is typically provided by both electricity and fossil fuels. Currently used fossil-fuels for mining are coal, natural gas, and oil products (McLellan et al., 2012). A significant share of fossil-fuels is transformed into motive power, for loading, hauling and trucking (Norgate and Haque, 2010). The rest is used to produce thermal energy, which is required for smelting the mineral concentrate.

Renewable sources can produce heat - biomass, solar, and geothermal - and could be potentially used for smelting. However, thermal energy usage for smelting of non-ferrous metals is typically high temperature. Renewable sources would not be able to provide such temperature - CSP can typically provide heat up to 350°C - but they could still be used as heat booster to alleviate a fraction of the fossil-fuel use (Hu et al., 2010).

Another application for heat in mining is to use it as a storage medium before conversion to electricity. Concentrated solar power (CSP) offers one of the most mature methods to create heat from direct sunlight, which can be stored in the form of heated liquid at a relatively low cost (Pihl, 2009; Herrmann et al., 2004). Combined heat and power (CHP) alternatives constitute another technological solution that can generate heat for mining processes.

1.3.4 *Mining power systems*

SYSTEM TYPE In mining, local power systems including renewable energy sources consist of two major types: off-grid and grid-connected. First, traditional grid-connected systems can be subdivided into two types: distributed and centralised. While a centralised system implies that renewable sources feed the central grid, a distributed system employs renewable sources to supply on-site power demand, and the remaining electricity is supplied to the grid (IPCC, 2011). Second, off-grid systems are remote or isolated systems that are not connected to the central grid. Off-grid systems are traditionally found when the connection to the central grid is not possible or too expensive (Misak and Prokop, 2010). Because these systems operate autonomously, they cannot rely on the grid to balance supply with demand. Instead, they must rely on their own balancing mechanism to control line voltage, frequency, and the overall adequacy of supply (Katiraei et al., 2007).

In the last decade, there has been an increasing interest for off-grid systems that include renewable sources, due to lower costs and the global push for reducing greenhouse gases. Those systems are composed of renewable energy technologies, and other energy sources for handling the intermittency - typically diesel generators but energy storage is another alternative. Several studies have investigated such systems for rural electrification (Miller and Hope, 2000; Shaahid and El-Amin, 2009) as well as for supplying electricity to off-grid islands (Ustun et al., 2011); but little interest has been shown for mining activities. Yet, as more and more mining operations move to off-grid locations - due to the depletion of the easily accessible mining reserves - the access to environmentally friendly and affordable energy sources is becoming a significant issue (Paraszczak and Fytas, 2012). As a result, remote mines without grid infrastructure are prime candidates for stand-alone hybrid renewable systems.

Alternatively, renewable energy sources can be implemented to supply grid-connected mines; therefore forming a distributed network. In simple terms, a distributed network is an "electric power generation within the distribution networks or on the customer side of the network" (Ackermann et al., 2001). This type of power system can be very complex to integrate into traditional transmission and distribution networks. However, in mining context, the generated power and heat are mostly or totally supplied to the mine, which means that these integration problems should be less predominant. Yet, large-scale distributed power affects the network in other ways. Among others, if the network demand is lowered, the grid generation plants would require more fuel per kWh due to part-loading, and lower efficiencies (Najjar, 2001), which should ultimately affect the electricity prices of the grid.

technology Even when there is an abundant availability of intermittent renewable sources, a solar or wind stand-alone system cannot satisfy the load on a 24h basis. Stand-alone diesel plants can deal with intermittency but they are generally expensive to operate - high fuel costs and high price uncertainty - and are contributing to carbon emissions. Other solutions include energy storage technologies or hybridized systems including renewable, storage, fossil-fuel generator, and potentially grid connection (Shaahid and Elhadidy, 2007).

While most energy storage plants have been previously built to provide baseload or power quality services, there has been a renewed interest in these technologies in order to balance intermittent electricity generation technologies such as wind or solar power. The current global landscape of energy storage consists mostly of pumped-hydro systems, accounting for over 99% of total storage capacity. The remaining 1% includes compressed air energy storage, sodium-sulphur batteries, and a few other one-off installations for other storage technologies (Deane et al., 2010).

Despite being the leading storage technology, pumped-hydro systems are characterised by a number of limiting factors for mineral production: site-specific, usually high capacity, and long lifetime (Rastler, 2010). These criteria might not be suitable for mining activities. For instance, a mine lifetime might be considerably shorter than a pumped-hydro scheme, or a mine might not be closely located to a suitable site for the reservoirs. Other recent technologies, however, seem worth investigating for renewable integration in mining.

1.4 summary of mining specificities

Several additional mining specificities have been identified in this thesis in chapter 2 on page 17 and 8 on page 213. A summary of major specificities is provided as follows.

1. The load curve and the load duration curve of the mining power demand are dissimilar to many other sectors. For instance, in contrast to residential load curves, the mining industry requires a relatively constant amount of power at all times. On that point, there is no down time in which the power demand is significantly lowered (as shown in section 3.9 on page 72).

2. Geographical characteristics of the mining industry cannot be chosen by the mining company; they only depend on site locations where significant amount of mineral ore is found. As a result, mines are often located in remote areas that do not have an appropriate energy infrastructure, and therefore commonly use off-grid systems to power their operations.
3. The industry is subject to geological and commodity price uncertainties, which implies that the expected mine-life is of great significance in the investment decision (as discussed in section 8.2 on page 214).
4. The mining industry is characterised by high energy demand and often large renewable resources at mine sites (e.g. high solar irradiance for Chilean and Australian mining industry). In this context, there is a potential for both higher returns and economy of scales that might not be applicable to other sectors.
5. There is a range of mining processes that are potential candidates for demand-shifting - which can in turn reduce the storage size (as discussed in section 5.3.2.2 on page 137).
6. Mining activities present different reliability costs than other industries (as reviewed in section 2.3.3 on page 30), hence implying that system sizing and reliability analyses need to be treated differently from other industrial activities.

Together, these factors justify the need to perform specific analyses that can accurately characterise the economic potential of hybrid renewable systems for mining settings. In turn, a literature review is undertaken in the following chapter in order to describe the current state of knowledge on the economic assessment of hybrid renewable power systems.

Part I

LITERATURE REVIEW

2

LITERATURE REVIEW

A literature review is undertaken in this chapter with the aim of describing the current state of knowledge on the economic assessment of hybrid renewable power systems. First, a background on hybrid renewable systems is provided in section 2.1. Second, the different approaches for determining the optimal system size, configuration, and application for hybrid renewable systems are discussed in section 2.2 with respect to their relative strengths and weaknesses. Third, the past research on power reliability, in terms of capacity adequacy and system security, are discussed in section 2.3 with regard to distributed and off-grid power systems. Fourth, the relevant research papers on decision-making and risk analysis for energy systems are reviewed in section 2.4. Finally, the chapter ends with a critique of the current literature in section 2.5 with respect to the research questions of this thesis.

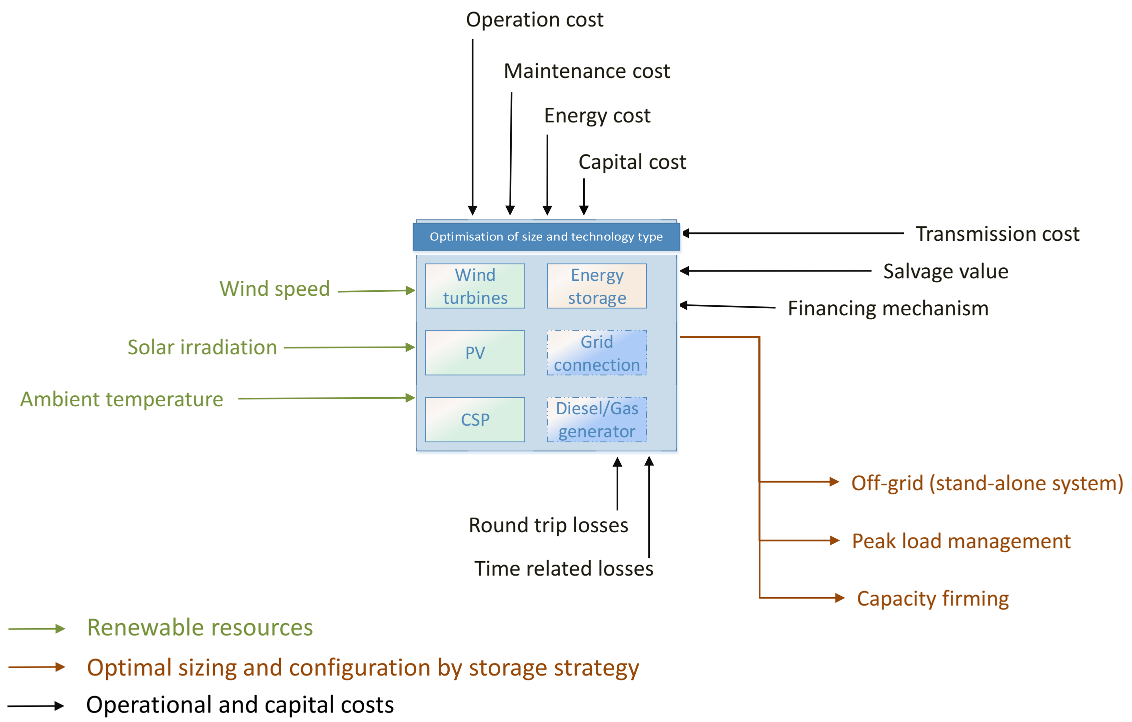
2.1 BACKGROUND ON HYBRID RENEWABLE POWER SYSTEMS

Energy systems that include two or more energy sources with at least one renewable energy source are defined in this thesis as hybrid renewable power systems. Different types of energy sources can be included such as renewable, energy storage, and conventional sources (i.e. grid, diesel). Energy storage technologies are usually implemented to handle the intermittency of renewable sources (i.e. solar, wind) and enhance system reliability (Luna-Rubio et al., 2012). Overall, these systems can sometimes present lower costs and higher reliability than traditional systems that include only one source of energy (Yilmaz et al., 2008; Dalton et al., 2009).

Hybrid energy systems can operate in either off-grid or distributed settings. In off-grid systems, the energy is produced independently of the grid by a stand-alone system. Energy storage is most often found in this configuration due to the intermittent nature of renewable sources (Celik, 2003). Additional generators using diesel or natural gas can also complement the output and enhance system reliability (Huneke et al., 2012). Because there are no external balancing mechanisms (i.e. grid), the issue of reliability and resource adequacy is particularly important for off-grid settings (Kaldellis et al., 2009).

In distributed settings, the grid is used to balance the local system and/or to enhance the output. Energy surplus can also be fed to the grid so as to avoid spillage costs and potentially generate revenues. Furthermore, energy storage can be implemented to firm-up the renewable output and provide an auxiliary source of energy (Korpaas et al., 2003). However, the size of storage plants in distributed settings tends to be smaller due to the availability of grid power.

Figure 2.1: Endogenous and exogenous parameters of hybrid renewable systems



Ultimately, the cost effective design of hybrid renewable power systems is very complex due to several prominent problems:

1. Hybrid energy systems are capital intensive, especially for renewable generation and energy storage
2. The desirability to match the load with intermittent outputs, while minimising the amount of energy storage
3. The conflict between the aim of minimising storage and maintaining an adequate level of reliability

4. Different risks are associated with different system configurations

The choice of the system depends on a number of endogenous and exogenous parameters, which are represented in figure 2.1 on the preceding page. Because of their complexity, the design of these systems can be achieved with an optimisation model that takes into account the appropriate system constraints and parameters (Luna-Rubio et al., 2012). In turn, the different optimisation methods are reviewed in the following section.

2.2 OPTIMISATION MODEL

The accurate sizing of every system component is critical for the techno-economic assessment of the whole system. As a matter of fact, the amount of economic benefits is significantly associated with the chosen sizing methodology for designing the system (Luna-Rubio et al., 2012). Specifically, the designing of such system refers to the search for the best configuration, in terms of size and components - which involves the selection of objective functions, decision variables, and optimisation constraints. The inclusion of renewable increases the complexity of the problem because of intermittent resources and non-linear characteristics. Furthermore, energy storage technologies are associated with high capital and maintenance costs, which lead users and investors to formulate complex problems to determine the least-cost size and technology associated with their energy requirements.

In order to provide the best economic value and the required reliability, the design phase of hybrid energy systems is based on an optimisation problem. In previous research papers, a large variety of optimisation techniques has been applied to these systems.

System behaviour is stochastic in nature, and it appears logical to use the relevant techniques (i.e. probabilistic) for assessing such systems (Billinton et al., 1996). Yet, deterministic methods are still largely employed by utilities to assess power systems. For instance, simple sizing methodologies have been applied to this problem, such as the averaging of weather data (Celik, 2003; Protogeropoulos et al., 1997). Similarly, a number of commercial studies have assessed these technologies with simple analytical methods. In these methods, hybrid energy systems are assessed for a set of possible system configurations and types of equipment. Best configuration is determined based on a single price index. In this context, the justification for using a more sophisticated approach is that higher levels of complexity are required for more objective assessments. A quote from Calabrese (1947) further reflects on the choice of methodology:

> "A fundamental problem in system planning is the correct determination of reserve capacity. Too low a value means excessive interruption, while too high a value results in excessive costs, The greater the uncertainty regarding the actual reliability of any installation the greater the investment wasted.
>
> The complexity of the problem, in general, makes it difficult to find an answer to it by rules of thumb. The same complexity, on one side, and good engineering and sound economics, on the other, justify the use of methods of analysis permitting the systemic evaluations of all important factors involved. There are no exact methods available which permit the solution of reserve problems with the same exactness with which, say, circuit problems are solved by applying Ohm's law. However, a systemic attack of them can be made by judicious application of the probability theory."

Consequently, a vast numbers of algorithms have been applied in order to deal with the complexity of power systems, including linear programming, quadratic programming, and various heuristic approaches (e.g. particle swarm optimisation, genetic algorithm). Most of these algorithms aim at reducing costs or environmental impacts. Traditionally, these approaches have been using long time series of climate data (for renewable sources) and load profiles - which also increases the complexity of the optimisation problems. A selection of the most distinctive ones appears in Banos et al. (2011).

Whilst past studies have not considered the specificities of the mining industry, many authors have addressed the sizing assessment of hybrid renewable power systems for different contexts. Therefore, in this section, the references associated with system sizing that support the discussions and theories of this thesis are reviewed. The section is organised around four major techniques: linear programming, non-linear techniques, dynamic programming, and heuristic approaches. This classification was made according to the complexity level of each optimisation method. Other types of classification have also been proposed in Luna-Rubio et al. (2012) and Banos et al. (2011).

2.2.1 *Linear programming*

As mentioned previously, a primary interest is to select the least cost-alternative in terms of size, technology, and control strategy. Some authors have solved this problem by applying linear programming (LP) techniques to determine the solutions that provide the desired energy services with minimal cost. In a nutshell, the LP technique is an optimisation method applied to problems with linear objective functions and linear constrains. This means that the net output caused by input variables is the sum of the outputs caused by each input variable individually (Illingworth, 1991). This method is built on various fields of research such as mathematics for the formulation of the model, computer science for coding the algorithms, and additional fields related to the problem being optimized (e.g. economics, engineering). Numerous studies have applied LP for renewable and storage systems; a review of the relevant LP studies is provided as follow.

On the one hand, some authors have applied LP technique in the context of a distributed power system in order to determine the optimal size under various system conditions. For example, Nottrott et al. (2013) have used LP under MATLAB to model the optimal storage dispatch schedules for peak load management and demand charge minimization in a grid-connected system combining battery and PV. They found that the net present value (NPV) of the battery system and battery lifetime were significantly improved with the forecasting of time of use (ToU) prices. However, their results ultimately showed that Lithium-Ion batteries are a financially viable option - in demand side applications - at an installed cost of \$400 - \$500 per kWh of capacity, which represented around 40-50% of 2011's price level. Alternatively, Barton and Infield (2004) have considered the possibility of increasing renewable generation and energy storage on weak electricity grids. Specifically, the investment criterion in their model was based on capital deferral for transmission lines. They found that storage options over long periods (i.e. 24h) with redox flow cells were able to allow 25% more of the wind energy to be absorbed without grid reinforcement but were not economically viable. Conversely, short term storage - using flywheels - allowed 10% more of the wind energy to be absorbed and provided significant economic benefits to the electricity system.

On the other hand, off-grid power systems have also been the focus of LP studies for determining the system size, independently of grid supply. For instance, Abbey et al. (2008) proposed an analysis of stand-alone power systems with wind generation and energy storage. They found that, at current storage prices, there is an economic benefit to install energy storage when the wind penetration reaches 60 to 80% of the power demand, and the economic benefit starts decreasing beyond 80%. Because diesel generators can be a significant source of carbon emission, a subsequent study have examined whether it is beneficial to maintain them in such system (Huneke et al., 2012). As a result, they proposed that it is preferable to maintain a limited capacity of diesel power in off-grid power systems in order to reduce storage costs and provide additional back-up capacities. Interestingly enough, the study found that technological preferences were highly sensitive to fuel prices, hence emphasizing the role of microeconomic factors on the take up of renewable and storage systems.

Alternatively, other authors have investigated alternative storage technologies with LP algorithms. For instance, Zoulias and Lymberopoulos (2007) have provided a techno-economic comparison of an existing hybrid stand-alone power system and hydrogen-based power system. They found that, while it is technically feasible to replace fossil fuel based gensets with hydrogen-based systems, it requires a 50% cost reduction on electrolysers and 40% on hydrogen tanks to be economical. They also stressed the importance of sizing and found that gensets and battery banks can be replaced with fuel cells by oversizing the renewable energy system (PV array in this study). In addition, simple optimisation methods have also been applied to provide visual tools that can help the optimisation process. For instance, Mohammad Rozali et al. (2013) have developed the numerical power pinch analysis in order to consider the energy losses of hybrid power systems. The authors argued that different types of appliances use different type of power; for instance, some appliances are AC and others are DC. As a result, they proposed that the application of their methodology can avoid unnecessary power conversion and reduce the optimal storage capacity in hybrid power systems.

However, a major limitation of linear methods is that they cannot represent accurately physical systems, which are generally non-linear (e.g. part-load efficiency of fuel plants). As a result, other optimisation methods have been applied to take into account non-linear characteristics.

2.2.2 *Nonlinear programming*

On the storage side, typical nonlinear characteristics include operation costs and storage efficiency. First, as opposed to most variable costs, the maintenance costs of energy storage technologies tend not to be proportional to its usage in kWh but rather depends on the cycling type (e.g. deep versus short discharges). Second, the storage efficiency for battery technologies widely varies with the pulse factor (Kazempour et al., 2009). This refers to the amount of power discharge in comparison to the rated capacity. For instance, NaS batteries can instantaneously discharge power from one to five times their rated storage capacity - if the AC-DC converter is adequate. However, higher rates of power discharge results in more power losses, and nonlinear efficiency rates.

Some authors have applied nonlinear programming techniques to account for these technical characteristics. For instance, Kazempour et al. (2009) have developed a self-scheduling approach under GAMS for the operation of NaS batteries and pumped-storage plants with considerations for the non-linearity of maintenance cost and storage efficiency. They found that the internal rate of return (IRR) was 29% for pumped-hydro, and 17% for NaS battery plants. Alternatively, Kongnam et al. (2009) have used mixed-integer nonlinear programming to determine the optimum generation capacity of wind farms, with the aim of maximizing profit-to-cost and profit-to-area ratios. The optimisation problem was formulated in order to select the optimal technological type and size with regard to operation costs, maintenance costs, and available area. Nonlinear elements of wind turbine operations such as cut-in and cut-out wind speed were considered in the model. Weibull and Ryleigh distributions were used to model the wind speed uncertainty, using hourly data at Phuket wind station in Thailand. As a result, they found that the NPV of wind turbines was associated with both investment capacity and turbine sizes. Specifically, larger wind turbines were more advantageous for scenarios with limited investment funds.

While nonlinear methods present a number of advantages (e.g. better accuracy in modelling) in comparison to linear programming, they tend to be computationally intensive when stochastic parameters are included in the model design. Consequently, other techniques have been developed to reduce the computational time (i.e. dynamic programming, heuristic methods) and integrate higher levels of complexity. In turn, these methods are reviewed as follow.

2.2.3 *Dynamic programming*

Dynamic programming (DP) is another optimisation method applied to solve complex problems, which can account for non-linear parameters. Typically, it is performed by breaking a problem into a number of simpler sub-problems. This method seeks to solve each problem only once and therefore reduces the computational time to determine the optimal solution (Sniedovich, 2010). A number of past studies have applied this algorithm to determine the optimal capacity size of energy systems.

For instance, Li et al. (2009) have explored a novel hybrid system including hydrogen fuel cell for long-term storage and battery banks for short-term storage. Based on DP, they have determined the optimal system configuration with regard to system costs and system efficiency. On the economic side, they measured the cost/benefit potential of the different systems, including fixed costs, variables costs, and levelised cost of electricity. On the engineering side, the study applied three different efficiency metrics, including total system efficiency, loss efficiency (i.e. dump load), and used efficiency (i.e. actual efficiency). Their results suggested that coupling hydrogen and battery storage enables higher system efficiencies and lower costs than traditional off-grid systems.

Korpaas et al. (2003) have applied a DP algorithm for the scheduling and operation of energy storage for wind power plants. Wind forecasting was used to determine the next day storage capacity. As a result, they suggested that energy storage can increase financial revenues by taking advantage of price fluctuations. However, electrochemical energy storage was found to be more expensive than grid reinforcement. It was also proposed that energy storage can be more advantageous where grid extensions would lead to adverse consequences on the local environment. Similarly, Lund et al. (2009) have applied DP to identify the best dispatch strategy of a compressed air energy storage plant. Their simulations aimed at determining the revenues generated by storing electricity when prices are low and discharging it when prices are high (i.e. peak load management). This study identified two operational strategies in order to maximise revenues. In one strategy, historical prices serve as the basis of price forecasting (former 24h). In the other strategy, the future prices of the next 24h consist of a price prognosis, which is a probabilistic calculation based on the hourly minimum and maximum bidding prices of the electricity market. This later strategy was found to provide significantly higher revenue for the CAES plant's owner. Yet, because future electricity prices are inherently unknown, they found inconsistent year-on-year revenues.

Alternatively, Kaldellis et al. (2009) have used a similar iterative approach to assess the payback of stand-alone hybrid energy systems, including PV and battery storage. As expected, they found that local solar conditions are a remarkable influencing factor of life cycle costs. Interestingly, they proposed that battery storage exceeded 27% of their system costs, which emphasised the difference between stand-alone and grid-connected systems. Finally, some authors have suggested that heuristic methods can offer shorter computational time than dynamic programming - especially when stochastic parameters are included (Tsung-Ying, 2007). In turn, the relevant heuristic studies are reviewed as follow.

2.2.4 *Heuristic approach*

Some authors have proposed approximate techniques to reduce computational time, such as heuristic methods and artificial neural networks - rather than traditional optimisation methods (Banos et al., 2011). Those approaches reduce the computational time by only assessing a fraction of the solution space, hence implying that the solution is not guaranteed to be optimal. Heuristic approaches have been successfully applied to multi-objective problems, such as the combination of minimising cost and reducing carbon emissions.

Typically, multi-objective optimisation consists of two main methods: aggregate-weight function and Pareto-based optimisation (Zitzler et al., 1998). On the one hand, aggregating functions combine all the objective functions in a single objective function, where the weight of each objective is adjusted according to its importance. While aggregating functions are relatively easy to model, they suffer from several weaknesses, such as that it can be very delicate to adjust the weight of the objectives when they are measured on different scales. On the other hand, Pareto-based multi-objective techniques address such weakness by linking various solutions according to the Pareto-dominance concept. That is, the solution S_1 dominates the solution S_2 when S_1 offers a better result in at least one objective, and not worse in the others. This method generates a set of non-dominant solutions (termed Pareto optimal set) rather than a single solution.

Subsequently, multi-objective algorithms have been used for stochastic energy problems including probability density functions for renewables, or probabilistic price forecasting. For example, Lee and Chen (2009) have applied the evolutionary particle swarm optimisation (EPSO) technique to investigate the optimal contract capacities and installed capacities of a wind and PV generation system for time-of-use rate industrial user. The program HOMER was used to generate wind speed probabilities using a Weibull distribution. They suggested that the most critical influencing factor of the benefit-cost ratio was the energy cost while the capital cost had the greatest influence on the optimal installed capacity.

Similarly, Wang and Singh (2007) have applied a fuzzified multi-objective particle swarm optimisation algorithm to investigate the optimal generation dispatch in electric power systems. Both aggregated function and Pareto-based methods were used to determine the best power configuration of generators, including costs and emissions as objective functions. However, no consideration was made for the stochastic elements related to system reliability. Consequently, in a following paper, Wang and Singh (2008) have included the system reliability among the objective functions. Specifically, they examined the trade-offs between system risk and total running costs - by including the impact of wind power intermittency on the system. A set of non-dominant Pareto-optimal solutions was provided in relation to reserve constrains and transmission losses. Interestingly, they also considered the attitudes of dispatchers towards wind power, with different functions representing an optimistic, neutral, and pessimistic attitude. They suggested that the optimistic design provided the highest benefits, with a larger amount of wind power among all three attitudes. Finally, they stressed the importance of the relationship between energy reliability and power balance constrains. Alternatively, Tsung-Ying (2007) proposed a multi-pass iteration particle swarm optimisation algorithm (MI-PSO) to determine the optimal dispatch power of a battery storage system and wind turbine generators for a time-of-use rate industrial user. Weibull probability density functions were generated with the software HOMER to assess wind speed probability. As a result, they suggested that higher profits can be generated by accounting for load uncertainties. To conclude, heuristic approaches have proven to be useful in order to reduce computational time in past studies.

2.2.5 *Strengths and weaknesses of optimisation approaches*

The cited references show that various methods can be applied to solve the same problem. However, each of them encompasses a number of limitations. The simple methods, including averaging and worst case scenario, have not been considered in previous studies because they are limited by the use of short time series. This implies that the modelled results tend to favour an oversizing of the system, which therefore reduces the economic benefits. Alternatively, sizing approaches based on linear programming have been extensively applied for renewable and storage generation. However, the biggest disadvantage of linear techniques is the inaccurate assessment of storage systems that present non-linear characteristics. For instance, maintenance costs and storage efficiencies do not vary linearly for battery storage. Subsequently, nonlinear techniques and dynamic programming have been applied to take into consideration nonlinear parameters. These approaches can effectively take into consideration the characteristics of energy storage technologies - especially battery storage - and therefore provide more accurate results.

However, a major limiting aspect for these methods is the high computational time and the lack of consideration of randomness in the sizing of power systems. This is particularly important for optimising power generation with uncertain fuel prices and intermittent resource inputs. Yet, a certain amount of randomness can be included in the previous approaches but it usually leads to unacceptable computation times. In this context, approximate approaches (i.e. heuristic) have overcame this problem by not calculating all the possible solutions to find the best alternative. Rather, these techniques generate a set of solutions along an optimisation trajectory - hence drastically improving computation time. Finally, the issue of reliability cost and reliability worth further increases the complexity of the sizing problem. In turn, this matter is reviewed as follows.

2.3 Reliability analysis

Traditionally, there is a need for the system operators to understand the power quality of the system for which they are responsible. Because of the intermittent nature of wind speed and solar radiation, a critical aspect in designing hybrid renewable power systems is the reliability of supply (Kashefi Kaviani et al., 2009). The concept of reliability relates to the ability of any system to perform its intended function. In the case of power systems, the primary function is to provide adequate and secure supply of electricity to the users. In this definition, the adequacy refers to the existence of sufficient capacity to meet the system demand, while security refers to technical perturbations including system failures and malfunctions (Kariuki and Allan, 1996). Both considerations are important to assess the reliability of power systems but the adequacy assessment is particularly critical for intermittent energy sources.

2.3.1 *Reliability assessment methods*

There are three main approaches for assessing the reliability of power systems: deterministic, probabilistic, and stochastic based on Monte Carlo analysis (Georgilakis and Katsigiannis, 2009). Deterministic approach is based on fixed capacity margins, and fixed outage rates whereas probabilistic perspectives are applied when the uncertainty of customer load and generation capacity are of particular interest. Alternatively, Monte Carlo simulations can take into account the randomness associated with generation systems, including contingencies and operating characteristics. In theory, these simulations can assess system effects that would not be possible without considerable approximation in traditional probabilistic methods.

Numerous authors have performed reliability assessments in order characterise the availability of distributed and off-grid systems. Specifically, (Giorsetto and Utsurogi, 1983; Wang et al., 1984; Billinton and Chowdhury, 1992) proposed a multi-state approach of wind turbine generation in order to probabilistically evaluate different energy states including power output and forced outage rate. Other authors have extended the multi-state approach for assessing the probability associated with each battery state (Paliwal et al., 2014b,a). The authors observed that such method was able to deal with the complexity related to both renewable energy generation and battery storage, and requires less computation power than Monte Carlo approaches. Others have applied load adjustment approaches to eliminate the power output from the grid, and then use the adjusted load to assess the reliability of renewable sources (Marsh, 1979; Singh and Lago-Gonzalez, 1985). Similarly, Karaki et al. (2000) have applied probabilistic methods to determine the wind turbine output based on a Weibull distribution of wind speed. The probabilistic study of Kaldellis et al. (2004) have concluded that capital cost is significantly reduced when the reliability value drops to 95% reliability - instead of 100% - in a stand-alone photovoltaic system. Tanrioven and Alam (2006) have used Markov chain to determine the probability of power output based on different system states such as up, de-rated, and down. Alternatively, (Roy et al., 2010) have proposed to incorporate the uncertainty of renewable output with chance constrains for a pre-specified reliability requirement. Their results stressed a number of interesting findings: a) the design space of hybrid power systems is comprised in the region between the maximum reliability limit and the minimum allowable reliability, b) for each value of reliability level, there is a different system design with a minimum storage requirement as a well as minimum and maximum generator ratings, c) for stand-alone renewable-storage systems, there is a limit for the maximum possible reliability value.

Other studies have applied non-sequential Monte-Carlo simulation approach to assess the reliability of power systems - thus only including uncorrelated generation states (Vallee et al., 2008; Wen et al., 2009). For instance, Vallee et al. (2008) have developed a two-state Monte-Carlo model for global wind production. They suggested that the spreading of wind turbines can reduce the probability of zero wind generation as well as increase the overall wind capacity. Alternatively, many authors have applied sequential Monte Carlo simulation in order to take into account the correlation between peak demand and renewable output. Specifically, Ming and Yichun (2006) have assessed wind-diesel energy systems with Monte Carlo for investigating the uncertainty of wind speed, system load, and failure rates. They proposed that wind power generation will become increasingly viable due the constant price escalation of fossil-fuels. Da Silva et al. (2007) have used Monte Carlo simulation to assess the behaviour of reliability metrics, including conventional loss of load indices and well-being assessment of power systems. They suggested that, in the European Union, it is necessary to oversize renewable capacity for reaching an acceptable level of power reliability. Finally, Wang and Billinton (2001) have proposed a time sequential simulation to investigate the reliability worth/cost associated with variable wind speed and forced outage rates. They emphasised that there is an important relationship between reliability indices and system sizing, and showed that time-sequential methods provide significant benefits for the sizing accuracy of renewable power systems.

2.3.2 *Reliability considerations*

Several types of power failures are considered in any reliability approach addressing security issues. For distributed and stand-alone renewable systems, those include independent failures, same cause failures, dependent failures, sensitivity to repair rates, and weather effects (Li, 2002). Some past publications have incorporated security assessment in sizing studies with consideration to forced outage rates and planned outage rates (Atwa and El-Saadany, 2009; Billinton and Karki, 2001; Karaki et al., 1999; Kashefi Kaviani et al., 2009). However, other studies have not considered security issues - only adequacy - because security effects were found to be relatively small (Georgilakis and Katsigiannis, 2009; Hu et al., 2009; Papathanassiou and Boulaxis, 2006).

Other studies have extensively investigated this matter with regard to the correlation of failure between different system parts as well as the cascading effect of a power failure onto the rest of the system. This task is relatively difficult to achieve because of the diversity and complexity of the underlying causes that can lead to both a positive correlation of failure and a cascading effect. A number of authors have investigated those issues from different perspectives. For instance, Melo and Pereira (1995) have proposed a novel methodology for calculating reliability indices such as LOLP (Loss of Load Probability), and LOLF (Loss of Load Frequency) - with regard to sensitivity analyses for repair rates and equipment failures. Their approach incorporates the effects of uncertainty and trade-offs between additional maintenance costs and failure rates. Alternatively, Li et al. (1995) investigated the trade-offs between the cost of transmission reinforcement and reliability indices. They suggested that, in the context of their case-study, it was preferable to defer transmission investment because non-investment alternatives (i.e. load management) provided a better economic return. Finally, Li (2002) presented a method that includes ageing failure as part of the reliability assessment. They argued that ageing failures have significant effects on reliability, and ignoring it can result in large underestimation of outage rates - and therefore system costs.

2.3.3 *Reliability cost and reliability worth*

Depending on the level of reliability requirements, it might be necessary to increase the system capacity, and therefore increase investment costs (Allan and Billinton, 2000). This is of particular interest because financial implications are of great importance for all investors, including the mining industry. This problem of system reliability versus capital investment has been considered by various studies. Usually, this has been done by seeking the best compromise between reliability cost and reliability worth. That is, investments on increasing capacity (i.e. reliability costs) are only made if they provide enough economic value (i.e. reliability worth). The reliability costs are obtained from traditional system analysis - such as optimisation models. However, reliability worth is a much more complex problem because power costs are not always quantifiable and depend on various qualitative factors, including inconvenience or irritation. In the past, various reliability assessments have been performed, many are discussed in Wacker and Billinton (1989); Balducci et al. (2002); Lawton et al. (2003).

Among those, a number of comprehensive surveys have been performed in Canada, UK, and the U.S.A. Particularly interesting to note is that reliability worth studies are usually based on customer perceptions for the domestic sector and the Ratio of Gross Economic Output to Energy Consumption for the industry. For instance, the University of Saskatchewan published a number of sector customer damage functions (SCDF) to represent the average costs that an average customer would incurred per kW of peak annual demand (Billinton et al., 1993). In the industrial sector, they proposed that this cost varied from 1.6 \$/kW for a 1 min interruption to 55.8 \$/kW for 8 hours. In the UK industrial sector (Kariuki and Allan, 1996), the SCDF estimates ranged from 6.15 \$/kW for a 1 min interruption to 150.4 \$/kW for 8 hours. Interestingly, the UK study also provided estimates in terms of aggregated annual consumption, and found that this reliability cost ranged from 3.1 \$/MWh for a 1 min interruption to 67.1 \$/MWh for 8 hours. Alternatively, the Pacific Northwest National Laboratory has provided reliability worth estimates at industry level based on a ratio comparing the total electricity usage and the total economic output (Balducci et al., 2002). They proposed that the interruption cost of the primary metals industry ranged between 1.34 $/kW for a 20 min interruption to 5.26 $/kW for 4 hours, and the cost can reach 205.85 $/kW for a 4 hours interruption in the oil and gas industry (see table 2.1). Various estimates can be derived from SCDF estimates, and one of particular interest for hybrid renewable systems is the value of lost load.

Table 2.1: Interruption cost for the U.S industrial sector in 1996 (US$/kW) (Balducci et al., 2002)

Industry	Duration of Interruption		
	20 Minutes	**1.0 Hour**	**4.0 Hours**
Agriculture – crops	0.02	0.12	1.28
Coal Mining	1.34	2.11	4.66
Oil and Gas Extraction	81.47	193.88	205.85
Food and Kindred Products	4.74	15.10	50.52
Primary Metals Industry	1.55	2.49	5.26
Industrial Machinery and Equipment	3.02	5.40	18.45
Electrical and Electronic Equipment	3.48	6.60	19.89

2.3.4 *Reliability metrics*

While SCDF estimates represent the cost per interruption per kW of peak demand, it does not put a value on an unsupplied kWh. For instance, based on the Canadian SDCF estimates, the cost of a 1 min. interruption for an industrial user with a 100 MW peak demand would represent $160.000 in 1996 ($1.6 per kW * 100.000 kW), but this method does not provide the cost of a partial outage - in this example, any value lower than 100 MW. This has been included in another reliability metric, termed value of lost load (VoLL). The VoLL is considered to be the cost that a costumer would incur per kWh unsupplied or kW interrupted (Allan and Billinton, 2000). This metric is therefore much more practical to use with intermittent systems, where the power supply can vary independently of the power demand. Interestingly, the definition of VoLL does not provide temporal and spatial information on the circumstances leading to the curtailment, but a variety of factors have been suggested to affect its value - including: activity curtailed, time of day, season, duration and number of curtailment, advance warning and cause of interruption (Kariuki and Allan, 1996). Some authors have mentioned some of these factors for the calculation of the VoLL. For instance, Kariuki and Allan (1996) have included the duration of curtailment to derive different VoLL curves, and Willis and

Garrod (1997) have suggested that advance warning, time of day, and annual outage frequency are important factors for valuing the VoLL.

The VoLL indicator is usually combined with probabilistic criteria to compare the total expected VoLL (EVoLL) with the cost of increasing capacity. These probabilistic criteria include a variety of indices such as Loss of Load Probability (LOLP), Loss of Load Expectation (LOLE), System Performance Level (SPL), Loss of Energy Expectation (LOEE), Energy Index of Unreliability (EIU), Energy Index of Reliability (EIR), and System Minutes (SM) (Allan and Billinton, 2000). Past research have applied these indices to assess the reliability of renewable power systems and energy storage systems. For instance, Maghraby et al. (2002) have assessed a photovoltaic and battery system with the LOLP and SPL indicators. While the LOLP index was used to measure the probability of the system not being able to supply the power demand for a given time, the SPL indicator used the Markov chain matrix to provide on overall probabilistic index of system failure. As a result, they suggested that LOLP was a better suited index because it provides information per unit time and therefore allows the operator to determine whether the period of lost load is important. However, LOLP defines the likelihood of power curtailment but not the amount of energy shortage. Consequently, some authors have combined the LOLP and LOEE indices to account for both the likelihood and intensity of curtailment. For instance, Hu et al. (2009) have used LOLP and LOEE to measure three storage control strategies associated with wind power and energy storage. Their study stressed that LOEE and LOLP are dependent on the system configuration, e.g. the LOEE tend to be higher when the storage facility is also used by the central grid, rather than being only used for renewable capacity firm-up. Such indicators of reliability can be considered by applying either deterministic or probabilistic approaches.

By contrast, Billinton and Karki (1999b) have proposed an alternative to the traditional probabilistic measurements of reliability. Their approach, termed well-being analysis, aims at providing richer information on reliability with regard to capacity reserves. In a nutshell, the well-being perspective suggests that a power system is considered healthy if there is sufficient capacity margin to meet the power demand. Initially, this technique combined simple deterministic criteria for loss of load probabilities and probabilistic criteria to assess the capacity reserves of the power system. This was extended by (Billinton and Karki, 1999a; Wangdee and Billinton, 2006) in order to account for the randomness of power outages in large power systems. In that sense, the power system is modelled in relation to random events that can change the level of system well-being - which is the difference between available capacity and power load. Interestingly, Da Silva et al.

(2007) have considered both conventional LOLE metrics as well as well-being indices for power systems including renewable sources, in a sequential Monte Carlo analysis. Together, the two approaches enabled an accurate characterisation of power reliability including both the number of hours spent on marginal states - as opposed to healthy power states - and the outage probability.

2.4 DECISION ANALYSIS

Decision analysis consists of a set of principles and theories for making decisions under different alternatives. Uncertainty and risk are the two main issues involved in decision-making. Uncertainty arises when the states of nature of each alternative are unknown and impossible to describe accurately. Various types of uncertainty can be considered for mathematical models, including aleatoric uncertainty and epistemic uncertainty (Kiureghian and Ditlevsen, 2009). Aleatoric uncertainty consists of the parameters that are always changing and cannot be predicted accurately. Epistemic uncertainty includes the parameters for which there are not enough data to provide an accurate measurement. Alternatively, risk arises when any type of uncertainty can lead to an undesired effect or significant loss (Laffont, 1989). Both concepts have been applied to the field of energy systems for decision-making.

Whereas climate parameters and energy security consideration constitute a well documented source of aleatoric and epistemic uncertainties (Boyle, 2004; Allan and Billinton, 2000), the case can also be made for other aspects: the uncertainties associated with fuel prices and technological costs. First, fossil-fuel generation and renewable generation are competing with each other, which could lead to opportunity costs if fuel prices were to change significantly in the future. Similarly, the introduction of various environmental policies can drastically increase the present value of renewable alternatives. Second, the technological costs of energy systems can fluctuate in relation to market condition, technological improvement, labour cost, and economies of scale; for instance, Nrel (2012) provides cost estimates of storage technologies with an error margin of +/-75%. Together, these factors provide a significant source of uncertainty for decision-makers, which can hinder the uptake of the most uncertain technologies.

In this context, different principles can apply to make decisions. First, the MaxiMin principle (or pessimistic decision making) encompasses to evaluate each alternative for the worst possible outcome. As a result, the optimal decision with the worst possible outcome is selected. Second, in contrast to the MaxiMin principle, the MaxiMax principle consists of evaluating alternatives for the best possible outcome, which is generally regarded as optimistic decision making. Third, the Hurwicz principle considers alternatives within these two extreme states (Arnold et al., 2002). Fourth, the Laplace principle or insufficient reason argues that without probabilistic information on the different alternatives, the best choice is to select the alternative with the highest average outcome (Sharma, 2001). Finally, the savage principle or MiniMax regret encompasses to construct a matrix with the opportunity loss (regret value) of each alternative, representing the differences between the best possible outcome and a given outcome. The matrix is then used in conjunction with risk probabilities for decision making (Loomes and Sugden, 1982).

These decision-making principles have been put into practice in various studies concerning technological choice or investment decision. For instance, Kongnam et al. (2009) have considered the MaxiMin, MaxiMax, Hurwicz, Laplace, and savage principles for determining the optimum investment decision for a 1 MW wind park, in relation to profit to cost and profit to area ratios. They found that these principles were able to distinguish two optimum investments among eight investment alternatives. Wang and Singh (2008) have investigated decision making for wind power under the Hurwicz principle. They proposed that risk levels for wind penetration were associated with the attitude of dispatchers towards wind power. Subsequently, they have provided cost estimates for each attitude in order to account for this epistemic uncertainty. Traditionally, authors have combined these three perspectives on uncertainty to let decision-makers use any of the MaxiMin/MaxiMax and Hurwicz methods. For instance, Denholm and Margolis (2007) have investigated the limits of solar photovoltaic in electric power systems and provided results with minimum, intermediary, and maximum values. Similarly, Korpaas et al. (2003) have reported a range of results regarding the predicted revenues of wind parks, including minimum, intermediary, and maximum revenues.

However, other studies have proposed to use comprehensive frameworks to facilitate decision-making (Pohekar and Ramachandran, 2004). The use of decision frameworks has a long history in energy projects. They typically aim at considering a range of conflicting factors, such as technological, economic, environmental, social, and financial risks. Specifically, decision frameworks such as multi-criteria decision aid techniques (Siskos and Hubert, 1983; Zhou et al., 2006) and outranking methods (Lahdelma et al., 2000) have been proven useful for improving decision-making. These approaches share common characteristics such as the aim to determine the most satisfactory and efficient solution, and conflicts among criteria such as incomparable units. Some authors have also taken into consideration the decision maker's preferences by the inclusion of economic utility functions (Afgan and da Graca Carvalho, 2000). However, this approach suffers from two major weaknesses: a) it requires extensive data collection, and b) the results are not easily generalisable. For instance, Haralambopoulos and Polatidis (2003) proposed an integrated decision-making framework for renewable energy projects. To find group consensus, their approach encompassed to use a mix of qualitative and quantitative data on decision-makers, which included local authorities, potential investors, government, and pressure groups (i.e. NGOs, media). Because their data were situated in a local context, the results of their study cannot be significantly extrapolated to other projects.

Finally, the risk factor associated with cost and return is another large area of uncertainty, which has been traditionally investigated by the literature on financial assets. In turn, this risk is reviewed in the following section.

2.4.1 *Risk analysis*

Under traditional engineering cost approaches, a risky cost stream has often the same net present value than a safer cost stream. This violates the finance theory, where the risk factor must be included in the valuation process (Awerbuch, 2000). In this context, some authors suggest that the risk on costs and returns can be addressed by diversifying the generation sources (Awerbuch and Berger, 2003; Jansen et al., 2006). This principle, called the Markowitz portfolio theory (MPT), has been initially introduced for financial assets (Markowitz, 1952). It suggests that by diversifying a portfolio of assets, the overall risk can be reduced in comparison to the risk of individual assets. From a theoretical standpoint, the basics of MPT are based on the mean-variance concept. It encompasses to put together a variety of assets in order to generate a minimum-variance portfolio for any given level of expected return or system cost. Such portfolio minimise risk, which is measured by the standard deviation of the periodic return or cost.

Energy investments are not too dissimilar than financial securities, where financial portfolios are constituted of a number of different assets in order to manage risks and maximise investor value. Similarly, electricity generation can be viewed in terms of different technologies, with different risks and financial performances. At any given time, some generation technologies may have high costs while others might have lower costs, yet over long period of time, the overall generation portfolio can be used to minimise the risk associated with each alternative (Awerbuch and Berger, 2003). Indeed, MPT suggests to evaluate the economics of traditional and renewable energy technologies not on the basis of their stand-alone cost, but based on their portfolio cost. Specifically, the main characteristics of MPT is to assess how particular alternatives can change the cost and risk of a portfolio of generation options.

Early applications of this theory in the energy sector have been introduced by Bar-Lev and Katz (1976). More recently, using traditional MPT principles, Awerbuch (2000) suggested that photovoltaic technologies, with higher costs than fossil-generation, can reduce the cost risk of a generation portfolio. Further, Awerbuch and Berger (2003) proposed that the important implication of portfolio-based analysis is that generation alternatives must not be evaluated by comparing stand-alone options, but by comparing alternative portfolios of resources. Subsequently, while Awerbuch and Berger (2003) have applied MPT in relation to expected periodic return (or holding period return), Jansen et al. (2006) have proposed some changes in the theoretical framework with the introduction of the concept of cost risk. Their approach expressed the risk factor in terms of costs instead of a percentage, which was suggested to facilitate the conversion between portfolio cost and portfolio risk as well as provide more useful indicators for decision-making related to energy systems. As a result, Jansen et al. (2006) suggested that renewable generation can greatly improve the cost risk and sometimes yield a significant risk reduction at no extra cost. For both approaches, the concept of efficient frontier (either in terms of costs or returns) was applied to determine which portfolio was considered efficient; that is, the optimal system alternative with regards to trade-offs between cost (or periodic returns) and risk (i.e. standard deviation and covariance). Ultimately, the concept of efficiency frontier was found useful to determine the optimal trade-offs between several generation portfolios.

More recently, the portfolio theory has been the object of increasing attention in the energy literature. For instance, Roques et al. (2008) have applied the mean-variance portfolio approach to a Monte Carlo simulation of a portfolio including gas, coal, and nuclear. They suggested that long-term purchase agreements can help to balance optimal portfolios towards larger shares of coal and nuclear plants - hence reducing the energy produced from natural gas. Delarue et al. (2011) proposed a new application of the portfolio theory to non-dispatchable and intermittent energy sources. Distinction was made between investment in capacity, electricity generation, and instantaneous power output. In contrast to the application of the standard portfolio model, they suggested that a larger share of renewable energies can be incorporated into the energy mix to reduce the mean-variance of the model. Finally, Zhu and Fan (2010) have evaluated the cost risk of the future generation portfolio of China for 2020 plans. In the carbon constrained scenario, they found that the generation cost risk of China in 2020 is even greater that in the 2005 portfolio. It was also proposed that renewable technologies require stronger policy support to increase their future uptake in China.

The cited examples shows that the application of the portfolio theory have only been applied to large power systems. To date, there are no studies that have considered stand-alone or small distributed systems from a portfolio perspective. Yet, there are no reasons why this theory should not be applied for such systems. Since hybrid renewable systems include at least two sources of energy, it is valuable to determine the optimal portfolio(s) of generation capacity that minimises costs and risks. This is particularly valuable for systems that include both renewables and fossil-fuel generation in which variable costs are usually associated with a wide range of risk characteristics.

2.5 SUMMARY

In this chapter, a review of the current state of knowledge on the economic assessment of hybrid renewable power systems was undertaken. Different approaches were identified that can be applied to investigate different perspectives on the economic competitiveness of such systems. Reviewed articles in this literature review have provided a number of cost estimates, insights, and methodological details with respect to optimisation, reliability, and decision-analysis for off-grid and distributed power systems. Among others, previous techno-economic studies that focused on hybrid renewable systems have considered off-grid tourist accommodations (Dalton et al., 2009), educational campus with time-of-use (ToU) pricing (Yilmaz et al., 2008), weak electricity grids (Barton and Infield, 2004), limited land available (Kongnam et al., 2009), industrial user with ToU pricing (Lee and Chen, 2009), and off-grid islands (Ustun et al., 2011). However, no previous academic studies have specifically assessed the economic competitiveness of hybrid renewable power systems for mining settings.

Another interesting consideration is the diverse range of economic results associated with hybrid renewable systems in previous publications (as shown in section 5.3.3 on page 140). While a number of studies have reported negative returns, other studies have found that those systems do generate positive returns. A number of reasons can explain this range of results. For instance, the use of different methods with different levels of technological details can lead to dissimilar results. Another explanation can be found in the consideration of different contextual factors across studies. For instance, some studies are based on industrial users while others use residential data under different climate conditions. As a result, the wide diversity of methodological completeness and the use of different contexts for similar technologies makes it difficult to generalise past results to the mining sector.

Given that the mining industry have different requirements than other industrial sectors (as argued in section 1.4 on page 13), a generalisation from previous studies cannot be performed and new analyses are therefore required in order to generate meaningful results. Subsequently, the first research question aims at performing an economic assessment of such systems by answering the following [1]: **To what extent can hybrid renewable power systems minimise electricity costs and reduce carbon emissions of the mining industry?** Based on the literature review on optimisation methods in section 2.2 on page 19, it was determined that the combination of storage and renewables in a small power system implies large uncertainties, and require the most complex optimisation methods. A heuristic optimisation algorithm has been therefore selected for this research - as detailed in section 3.3 on page 50.

In addition, past literature has identified different values of lost load for mining activities than other industries - see section 2.3.3 on page 30. This additional specificity of the mining industry implies that system sizing and reliability analyses need to be treated distinctively than other industrial activities. Based on the value of lost load of the mining industry (see section 6.2 on page 167), the second research question is stated as: **What is the optimal trade-off between capacity cost and reliability cost?** As the mining energy demand is characterised by a constant power load (as shown in section 3.9 on page 72), a deterministic adequacy approach was selected in order to characterise the impact of different resource inputs - the justification for this assumption is further discussed in section 6.1 on page 163.

A further gap in the current literature is the lack of consideration of stand-alone and distributed power systems from a portfolio theory standpoint. To date, energy portfolio studies have only considered large centralized power systems. Yet, this approach can be valuable for smaller systems that combine both conventional and renewable energy sources. The consideration of cost risk or return risk can provide unique insights on the

[1]Methodological details on each research question are given in 3.4 on page 51 while selected technologies that are considered to be part of hybrid renewable power systems are listed in section 4.4 on page 95.

risks associated with different energy mixes and different energy portfolios. As a result, the optimal configuration for a hybrid renewable power system can be chosen based on both cost and risk. In this context, the third research and final research question of this thesis is given as: **What is the influence of cost risks on the economics of such power systems?** This question examines different levels of risk associated with different unit costs. Finally, a decision-analysis based on the MaxiMin/MaxiMax principles (as reviewed in section 2.4 on page 33) is also applied with respect to the results of the portfolio analysis.

In turn, the modelling methods of each research question are provided in the following chapter.

Part II

METHODOLOGY

LIST OF SYMBOLS AND ACRONYMS

nk	Technological option selected from matric 3.3 with row n and column k
y	Size in kWh of a technological option nk
L_T	Project lifetime in years
h	hour
t	Year
I	Investment cost
OM	Operation and maintenance cost
F	Fuel cost
r	Real discount rate
E_{nk}	Energy output of a selected technology nk
E_S	Total energy output of all selected technologies nk
E_L	Mine power load
S_{max}	Maximum size in kWh per technological option
W	Wind turbine
W_{icy}	Wind turbine for icy climates
S_{PV^F}	Solar PV with no tracking (fixed)
S_{PV^T}	Solar PV with one axis tracking
$S_{CSP^{PT}}$	CSP parabolic trough
S_{CSP^T}	CSP tower
St_B	Li-Ion battery storage
FF_D	Diesel plant
St_H	Heat Storage (for CSP plants)

FF_{GT}	Gas turbine plant
FF_{CCGT}	Combined cycle gas turbine plant
FF_{G}	Grid supply
$y_{S_{CSP}}$	Size of the CSP plant (either parabolic trough or tower)
β	CSP solar multiple
κ	Minimum generation point in percentage of total power capacity
η	Conversion efficiency
M_{S}	Minimum guaranteed output of the local power supply
ϕ	Reliability coefficient
VoLL	Value of lost load
POR	Planned outage rate
UTCO	Portfolio unit cost (equivalent to LCOE)
EIR	Energy Index of Reliability

3

METHODOLOGY

The methodology chapter is used to describe the methods and underlying assumptions that are used to answer the research questions of this PhD. In section 3.1, the key modelling capabilities of the model that was developed for this research are detailed with respect to each research question. Major assumptions in terms of unit, time, system boundaries, and level of aggregation are subsequently provided in section 3.2 on page 48. Key mathematical equations and optimisation constraints are given in section 3.4 on page 51 for each research question. Further details are then provided for calculating system costs in section 3.5 on page 59, reliability measurements in section 3.7 on page 66, and portfolio modelling in section 3.8 on page 69. Extrapolation methods for determining energy demand are subsequently addressed in 3.9 on page 72. Finally, the modelling methods that have been applied to calculate and balance the energy outputs of all selected generation technologies are carefully detailed in section 3.10 on page 76. Note that data sources and additional parameters are provided in the data chapter 4 on page 91 along with a description of the selected mines for this research.

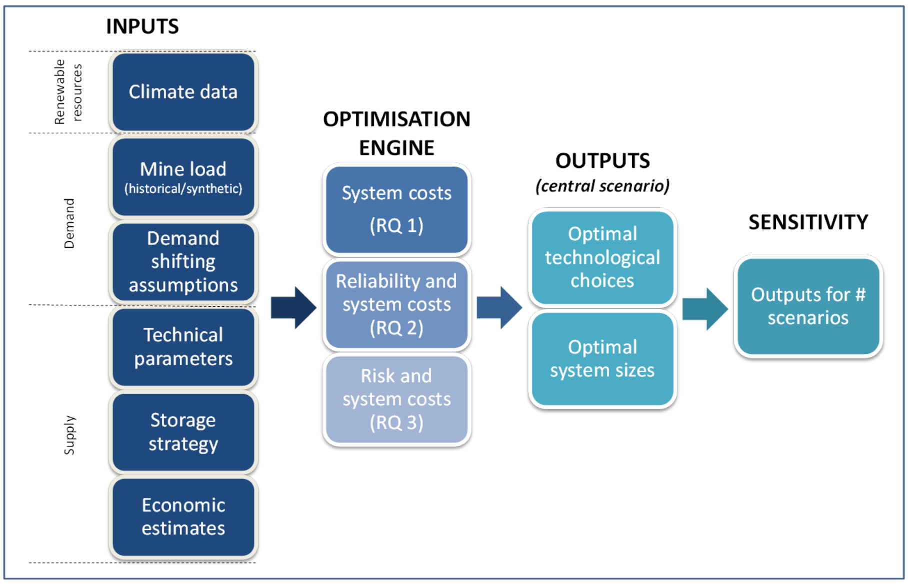
3.1 HELIOS-MINING CAPABILITIES

The Hybrid Energy Load Optimisation System for the Mining industry (HELiOS-Mining) is a model developed for this doctoral research. The development of this model has been necessary because it was determined that existing models are currently unable to take into consideration the three research interests of this thesis, namely: chronological optimisation at a high resolution, reliability optimisation, and portfolio optimisation (as reviewed in appendix D on page 305). More specifically, it was found that some existing models are able to answer some parts of the research questions (e.g. HOMER, EnergyPro) but none is able to answer all the research questions.

HELiOS-Mining includes on the following key capabilities - which are used for different research questions (RQ):

- Chronological simulation of the power supply of 12 different technologies at an hourly level (RQ 1, 2, 3).
- Detailed simulation of each technological option in relation to non-linear part-load efficiencies, power electronics, and rated outputs (RQ 1, 2, 3).
- Dispatch simulation of each selected technology with respect to electricity demand, cost, reliability, renewable resources, and storage cycles (RQ 1, 2, 3).
- Dynamic and static simulation of hourly mine power demand with respect to historical data and demand shifting assumptions (RQ 1, 2, 3).
- Simulation and economic valuation of total carbon emissions emitted/avoided against diesel or grid baselines (RQ 1, 2, 3).
- Least-cost optimisation of the power system in which up to four technologies can be combined together as a hybrid renewable power system (RQ 1, 2, 3).
- Least-cost optimisation of the power system in relation capacity margins and the expected value of lost load (RQ 2).
- Portfolio optimisation of different generation alternatives in relation to both average unit cost and cost variance (RQ 3).
- Determination of the efficient frontier with respect to a number of non-dominant generation portfolios (RQ 3).
- Decision-analysis with consideration to pessimistic and optimistic perspectives on fuel price, carbon price, and mine-life risk factors (RQ 3).

Figure 3.1: Key components of the research model HELiOS-Mining



The key components of the model are illustrated in figure 3.1. The methodologies and data-sources associated with each major component of HELiOS-Mining are given as follow:

- Climate data: data sources and methods used to compile and treat the data are provided in the data chapter of this thesis in 4.3 on page 94 and further discussed in section 6.1 on page 163 with respect to the adequacy analysis.
- Mine load: the power demand of each selected mine was determined based on historical data and synthetically generated data - methodological details provided in section 3.9 on page 72.
- Demand-shifting: assumptions that have been applied to model different scenarios in which the power demand is time-shifted are given in section 3.9.2 on page 75.
- Technical parameters: relevant technical parameters and modelling methods are provided in the supply section of this methodology chapter (see section 3.10 on page 76). Additional information on data sources are further detailed in the data chapter 4.5 on page 96.
- Storage strategy: this input is the mathematical description of the storage algorithms. The algorithms associated with the balance of the storage are provided in section 3.10.2 on page 78 whereas the implications of different storage strategies are discussed in section 3.10.1 on page 76.
- Economic estimates: the computation method used in the cost analysis is provided in section 3.5 on page 59 whereas economic inputs are provided in section 4.6 on page 101. Further methodological details are provided in section 3.7 on page 66 on the cost analysis of power reliability and in section 3.8 on page 69 on the cost risk analysis.

HELiOS-Mining was developed with three different tools in order to provide the appropriate answers to the research questions. First, Microsoft Excel was used for data treatment and as a graphical interface. Second, Python Excel (Pyxll) was used to develop the more complex algorithms of the model (e.g. storage algorithms). Finally, @Risk was selected for conducting the optimisation of the model and providing various outputs associated with uncertainty parameters (e.g. fuel cost uncertainty, stochastic runs). A description of the optimisation algorithm is provided in section 3.3 on page 50.

The overall system assumptions, research questions, and detailed objective functions of each research question are provided in the next two sections of this chapter in 3.2 on the following page and 3.4 on page 51.

3.2 OVERALL ASSUMPTIONS AND BOUNDARIES

The development of any model faces trade-offs between complexity and scale, which is dependent upon data availability and computation resources. A number of constraints and assumptions have to be made in order to generate insightful outputs. These assumptions provide a simplification of reality which is useful to understand complex systems and provide insights on optimal investment decisions (Godfrey-Smith, 2006; Weisberg, 2007). The description of the scale and level of complexity used in HELiOS-Mining are described as follows.

3.2.1 *Level of aggregation*

The model uses hourly data for both the demand and supply of electricity associated with the entire mine - as detailed in section 3.9 on page 72. In the demand-shifting analysis, the power demand is modified in order to account for different levels of demand-shifting - but the scale remains on an hourly basis. Limitations associated with the chosen time-scale are discussed in section 8.6 on page 222 along with other research limitations.

3.2.2 *System boundaries*

The scope of HELiOS-Mining is the manufacturing processes associated with the mining of non-ferrous metals. Whereas the reliability of the hybrid power system is analysed in the research question two from an adequacy perspective, the reliability of the grid supply is out of the scope of this research. Furthermore, it is assumed that the selected mines have not enough market power to alter electricity clearing-prices. This limitation has no impact on off-grid settings (three out of four selected mines).

3.2.3 *Time*

The model is able to simulate and optimise a power system for one year of operation on a chronological hourly level. Future years of operations are modelled on a year by year basis - extrapolated from the first year of operation. Yearly adjustments to demand and supply are performed with regard to degradation of efficiency over time - such as degradation of storage capacity. In this respect, it is assumed that the lost capacity associated with performance degradation is either balanced by the fossil-fuel plant, the grid connection, or by investing in new capacities.

3.2.4 *Units*

HELiOS-Mining is using a variety of technological costs expressed in USD_{2015}/kW of power capacity. The cost of energy storage technologies is expressed in both USD/kW for the power electronics and USD/kWh for the storage capacity. It is assumed that each component of the power system can be purchased at a kW or kWh unit. Economies of scale are considered when applicable - as detailed on table 4.7 on page 105.

3.2.5 *Existing power system at mine site*

This research focuses on assessing the costs of new power systems from a long-run perspective. It is therefore assumed that the current power costs of selected mines are considered to be variable. As a result, this research provides the system costs for a new installation that neglects the salvage value and depreciation costs of an existing off-grid power system. Further assumptions associated with existing grid power are given in the section 3.10.4.5 on page 90.

3.2.6 *Note on data and parameters given by the PhD industrial partner*

The M+W Group has provided several data points for this research due to a PhD partnership between M+W and the UCL Energy Institute. The cost estimates and technical parameters that were provided were sourced from industrial quotes or collaborative research projects between M+W and a number of institutions, such as the Fraunhofer Institute for Solar Energy Systems or the Lappeenranta University of Technology. In current and following chapters, the citation Engelhard (2016) is used whenever M+W data are used - Manfred Engelhard is the technology Manager of the energy division of M+W and was a key point of contact between UCL and M+W over the last three years.

3.3 OPTIMISATION ALGORITHM

HELiOS-Mining incorporates a number of non-linear functions to describe the technical characteristics of generation alternatives. It also involves a large solution space with several million of possible solutions associated with various combinations of technologies and thousands different sizing options for each technology. Furthermore, HELiOS-Mining is looking at both optimal configurations and near-optimal solutions - which provides an extra layer of complexity and exponentially increases the size of solution space. These features mean that the computational run time is not easily manageable with the common linear programming techniques found in various energy models. A meta-heuristic algorithm was therefore selected to perform the optimisation and reduce the computational run time of the optimisations. The OptQuest algorithm was chosen based on the review of Li (2013) in which a similar optimisation problem was performed, i.e. selecting cost-optimal heating technologies. OptQuest combines several optimisation algorithms such as tabu search, scatter search, integer programming and neural networks (Laguna, 2011).

Using the OptQuest algorithm, the computational time was reduced to 3-4 hours per run time. The work presented in this thesis is exploring the solution space with hundreds of optimisation runs performed over months of optimisation. All the analyses of this research were conducted multiple times in order to calibrate the model and mitigate the possibility of early convergence associated with the meta-heuristic optimisation algorithm. The optimisation process was automated by chaining macros together using a dedicated workstation with a fast height-core CPU. The mathematical problem definition of the optimisation including decision variables, constraints and objective functions is provided as follows for each research question.

3.4 RESEARCH QUESTIONS AND OBJECTIVES

3.4.0.1 *Research question 1 (RQ1) - To what extent can hybrid renewable power systems minimise electricity costs and reduce carbon emissions of the mining industry?*

The objective of this research question is to determine the least-cost system configuration in terms of system size and technological choice. As a result, the optimisation engine of HELiOS-Mining is subject to the following objective function and constraints for the first research question - the definition of each variable immediately follows and list of symbols is provided on page 43.

RQ1 objective function is given as:

$$J_{RQ1} = min \sum_{nk} \sum_{t=0}^{L_T} \frac{[(I_{nk,t} + OM_{nk,t} + F_{nk,t}] / (1+r)^t}{E_{nk,t} / (1+r)^t} \tag{3.1}$$

Subject to:

$$y_{nk} \in [0, S_{max}] \tag{3.2}$$

$$nk \in \begin{pmatrix} W & W_{icy} & & \\ S_{PV^F} & S_{PV^T} & S_{CSP^{PT}} & S_{CSP^T} \\ St_B & St_H & & \\ FF_D & FF_{GT} & FF_{CCGT} & FF_G \end{pmatrix} \tag{3.3}$$

$$y_{S_{CSP}} = \beta \cdot y_{St_H} \tag{3.4}$$

$$E_S \geq E_L \cdot \phi \tag{3.5}$$

$$\kappa_{nk} \cdot y_{nk} \cdot \eta_{nk} \leq E_{nk,h} \leq y_{nk} \cdot \eta_{nk} \tag{3.6}$$

$$\frac{[\sum_{nk} E_{nk,h}] - E_{FF_G,h}}{E_{L,h}} \geq M_S \quad \forall h \tag{3.7}$$

Where:

- In equation 3.1, the decision variable y_{nk} represents the size of each technological option in kW (or kWh for storage capacity). This variable is optimised in order to minimise the LCOE for the entire power system [1].
  - L_T is the lifetime of the technology or the lifetime of the mine (whichever is smaller), time is expressed in year t and hour h. I and OM are the annual investment costs and the operation costs - per kW (or kWh for storage capacity), and r is the real discount rate. FC is the cost per unit of energy input, E is the annual energy output, η is the conversion efficiency, and F represents the annual fuel costs (including carbon tax when applicable) given by:

$$F_{nk} = FC_{nk} \cdot \frac{E_{nk}}{\eta_{nk}} \tag{3.8}$$

  - In the constraint 3.2, the value of the decision variable y_{nk} is chosen between 0 and S_{max} - which represents the annual maximum cumulated electricity demand over 14 days. This value gives enough freedom to the model so that very large system sizes can be taken into consideration. For each technology that is not selected in the optimisation process, the value of the decision variable y_{nk} is set to zero.
- There are up to five technological alternatives in each category (noted n): wind (W), solar (S), energy storage (St), and fossil-fuel generation (FF) - as referred in the matrix 3.3 with row n and column k - see section 4.4 on page 95 for further details on selected technologies. The optimisation algorithm is allowed to combine technologies into a hybrid power system with no more than two technologies per category. This constraint ensures that all the relevant combinations are allowed in the model without requiring too much computational efforts. The choice is made by attributing a size y greater than zero to the selected technology. Note that the grid supply FF_G (i.e. existing grid and grid extension) is included in the fossil-fuel category (see section 3.10.4.5 on page 90 for justification).
- The constraint 3.4 ensures that if the heat storage alternative is chosen (in category St.) the concentrated solar power alternative (in the category S) must also be chosen. The coefficient β is the solar multiple associated with the CSP storage capacity. Other combinations of power technologies have not such constraint.

[1]
- Note that the selection of the LCOE as main economic metric is discussed in 3.6 on page 59.

- In constraint 3.5, E is the total energy supply of all selected technologies for the years t and hours h given by $E_S = \sum_{nk} \sum_{t=0}^{L_T} E_{nk,h}$ which is equivalent to:

$$E_S = E_{W_k} + E_{S_k} + E_{St_k} + E_{FF_k} \tag{3.9}$$

- The applied methodology to calculate the hourly output E of the technologies nk is given in the following sections:
  - Wind output $E_{W_k,h}$ at hour h is provided in section 3.10.3.2 on page 82,
  - Solar PV output $E_{S_k,h}$ is in 3.10.3.3 on page 83, and Concentrated Solar Power (CSP) is in section 3.10.3.4 on page 84,
  - Storage output $E_{St_k,h}$ is detailed in section 3.10.2 on page 78 - with respect to a charging and discharging algorithms,
  - Fuel-based power generation $E_{FF_k,h}$ is detailed in section 3.10.4.3 on page 87 for diesel and biofuel, and in section 3.10.4.4 on page 89 for gas turbines and CCGT.
- The dispatch priority of each technological group is set-up to prioritise non-dispatchable power generation and storage output - see section 3.10.4.2 on page 86.
- The total energy load E_L (constraint 3.5) is the sum of the power demand of hours h in year t. The modelling method for the energy demand is provided in section 3.9 on page 72.
- The Energy Index of Reliability (EIR) must be equal or superior to the variable ϕ (constraint 3.5) - this variable takes a different value in relation to various scenarios. This constraint ensures that the power system is able to meet the demand with minimal power break-downs.
- In constraint 3.6, κ_{nk} is the minimum generation point (as a function of the rated output), $E_{nk,h}$ is the hourly output, and η is the net efficiency of technology nk. Note that additional constraints apply to storage technologies - see section 3.10.2 on page 78.
- With respect to the constraint 3.7, M_S is the minimum guaranteed energy supply that must be generated in all hours h by the hybrid renewable power system (consisting of an optimal combination of technologies from the categories W, S, St, and FF).
  - This constraint aims at modelling the "capacity firming" storage strategy that requires a minimum guaranteed output at each hour t outside of any grid supply.

- This is assessed by comparing the variable M_S to the ratio of energy output E_{nk} and the energy demand E_L at hour h. Because the category FF includes grid supply, the energy output from the grid E_{FF_G} is subtracted from the total system output.
- The value of M_S is set to zero for all the other storage strategies (i.e. self-generation, net-metering).

Together, these variables allow the model to determine the minimum LCOE with respect to a number of constraints - which consists of a weighted average of the LCOE of all the selected technologies in relation to their sizes.

Further explanations on each of the cost variables associated with the LCOE are provided in the cost section of this chapter - see 3.5 on page 59.

3.4.0.2 *Research question 2 (RQ2) - What is the optimal trade-off between capacity cost and reliability cost?*

The objective of the second research question is to assess the trade-off between reliability cost and reliability worth. Specifically, this is performed by applying a value of lost load (i.e. reliability worth) on power shortages for several climate scenarios.

Note that this analysis aims a determining the least-cost amount of capacity margins that need to be installed, and it is not a precise engineering analysis of all reliability factors. As a result, a number of parameters (e.g. start-up, inverter) have been neglected in this analysis - and included in research limitations in section 8.6 on page 222.

The following objective function is considered for the second research question:

$$J_{RQ2} = min \sum_{nk} \sum_{t=0}^{L_T} \frac{\left[I_{nk} + OM_{nk,t} + F_{nk,t} + VoLL_{nk,t}\right] / (1+r)^t}{E_{nk,t} / (1+r)^t} \tag{3.10}$$

Subject to:

$$y_{nk,a} = y_{nk} \times (1 - POR) \tag{3.11}$$

Where:

- All the constraints of the first research question apply similarly to this objective function.
- VoLL is the Value of Lost Load for year t. This value is calculated by summing-up the value of foregone production for each unsupplied kWh - see 3.7.3 on page 67.
- The VoLL is considered to be an additional cost to the mine which increases the cost per unit of electricity (LCOE). In this respect, this problem remains a single-objective optimisation.
- The energy output $E_{nk,t}$ is based on different climate scenarios. Specifically, the output of solar and wind technologies are modelled according to the climate data of 10 different years (i.e. inputs), which are further detailed in chapter 6 on page 163 on adequacy analysis. The modelling method associated with the output E of technologies nk at time t is provided in the supply section (see 3.10 on page 76).
- In constraint 3.11, the planned outage rate (i.e. POR) is taken into consideration by subtracting the capacity associated with planned outage rate of technology nk from the rated power size - the justification for this hypothesis is given in 3.7.1 on page 66.

This research question provides insights on the trade-offs between system reliability and system cost. Because of the intermittency of renewable generation and the relatively high cost of energy storage, this question is particularly important to assess the impact of reliability costs on system unit costs.

Additional details and mathematical formulas are provided in section 3.7 on page 66 - including the hypotheses and mathematical formulas that were applied to calculate the VoLL.

3.4.0.3 *Research question 3 (RQ3) - What is the influence of cost risks on the economics of such power systems?*

The third research question is derived from portfolio theory (Awerbuch and Berger, 2003). Specifically, the objective of the final research question is to ascertain whether different system configurations have different risk profiles in terms of future costs. The risk associated with future costs (i.e. cost risk) consists of the standard deviation of future costs - where a number of cost assumptions are considered with respect to fuel costs, mine-life, and carbon taxation (as detailed in 7.1.1 on page 182).

Ultimately, this approach is able to determine a number of non-inferior generation portfolios (i.e. Pareto optima) which results in a number of possible solutions. Thus the outcome of this optimisation is not a single solution but a set of non-dominant solutions.

The objective function of the portfolio approach is provided as follows:

$$J_{RQ3} = min\ F(x) \tag{3.12}$$

subject to the following definitions:

$$F(x) = [AC_p, \sigma_p] \tag{3.13}$$

$$AC_p = \sum_{nk} X_{nk} \cdot UTCO_{nk} \tag{3.14}$$

$$\sigma_p = \sqrt{\sum_{nk} [X_{nk} \cdot \sigma_{nk}]^2} \tag{3.15}$$

and two additional constraints:

$$\sum_{nk} X_{nk} = 1 \tag{3.16}$$

$$X_{nk} \geq 0 \tag{3.17}$$

Where:

- F(x) is a vector of two objectives: AC_p is the average generation cost per unit of power for the portfolio p (which is equal to the portfolio LCOE), and σ_p is the standard deviation of the average cost of the portfolio p.

- X_{nk} is the share of the technology nk in the portfolio p. The total of the shares is equal to 1 (as given by constraint 3.16).
- $UTCO_{nk}$ is the average unit cost per kWh for the technology nk.

Different generation portfolios p are then sampled from the near-optimal space of the results of research question one. The applied methodology to select the portfolios p is presented in 7.1.1 on page 182.

The detailed steps that have been taken to determine the value of each of these variables are provided in section 3.8 on page 69.

3.5 system costs (rq1)

This section provides additional details on the calculation of system costs as well as further assumptions on financing, discount-rates and taxation.

3.6 measure of competitiveness

A number of economic measures can be applied to assess the competitiveness of power plants such as payback period, net present value (NPV), total life-cycle cost (TLCC), internal rate of return (IRR), or levelised cost of electricity (LCOE). The latter tend to be the most frequently used in the power sector in order to compare generation technologies on a cost per unit basis. The LCOE is also the chosen indicator of the mining sector because IPP agreements are negotiated on a price per unit basis over specific periods of time (e.g. mine-life). Numerous past studies have used the LCOE to report on the cost effectiveness of renewable technologies (Islegen and Reichelstein, 2011; Branker et al., 2011; Anderson, 2007). The consideration of the LCOE allows a consistent comparison across academic studies and provides a similar baseline for discussions with mining professionals. The LCOE is the chosen economic metric of this thesis. Other metrics have also been calculated when appropriate (e.g. total life-cycle cost).

3.6.1 *Levelised cost of energy*

In order to accurately calculate the costs of each technology, it is necessary to gather data on all the cash flows that occur during the mine lifetime (i.e. mine-life) or technological lifetime. Cash flows are usually taken into account in some aggregated form for each period of monetary accounting (i.e. investment years) - with different categories of expenditure. The chosen method for this model is the levelised cost of energy (LCOE) which represents the real value of each unit of energy output (Victor et al., 2014).

As per definition, the LCOE is "the levelised cost is the unique break-even cost price where discounted revenues (price x quantities) are equal to the discounted net expenses" (Moomaw et al., 2011) - which can be represented as:

$$\sum_{t=0}^{n} \frac{E_t \cdot LCOE_t}{(1+r)^t} = \sum_{t=o}^{n} \frac{(I_t + OM_t + F_t)}{(1+r)^t} \tag{3.18}$$

where I is the investment cost and the associated financing costs, OM are the operation and maintenance costs, F are the fuel costs, E is the energy output, and r is the real discount rate. Note that it seems as if the energy outputs E are discounted, but this is just the result of arithmetically rearranging the equation 3.18 and not an economic treatment of energy outputs (Branker et al., 2011).

Solving for LCOE and replacing n by the project lifetime L_T gives us:

$$LCOE = \sum_{t=0}^{L_T} \frac{(I_t + OM_t + F_t)/(1+r)^t}{E_t/(1+r)^t} \tag{3.19}$$

where L_T is the lifetime of the technology or the lifetime of the mine. The choice between these two lifetimes ultimately depends on whether the mining company can sell power to the grid or local communities once the mining company has fully exploited the ore available in the mine - both lifetimes are also expressed as the project lifetime. Because the length of the project lifetime can greatly influence the LCOE, a number of sensitivity analyses are performed on the basis of different lifetime values in section 5.3.2.3 on page 138. The calculation method for the real discount rate r is given in section 3.6.6 on page 65.

Details associated with each component of the LCOE are provided as follow.

3.6.2 *Investment costs*

The investment costs I are composed of capital costs as well as finance costs and decommissioning costs. Finance costs consist of the interests on overnight costs whereas decommissioning costs represent an extra capital cost that occurs at the end of the project lifetime, which is discounted to the initial year of the investment period. As a result, the calculation of the annual investment costs is as follows:

$$I = \alpha \cdot [C \cdot \sum_{t=0}^{L_b} (1+i)^t \cdot (1 + \frac{s}{(1+r)^{L_T}})] \tag{3.20}$$

where C is the capital cost per unit (kW/kWh) without the financing costs, and α is the capital recovery factor (CRF) - which is used to determine a unified stream of repayment over the investment periods. The financing costs on overnight expenses are equally distributed over the construction period $L_B$with the interest rate i for the construction loan. Typically, a rate of 5% is used for the financing of power projects (IPCC, 2011).

The decommissioning factor s is documented in the literature (Victor et al., 2014) as being only significant for nuclear energy options - which are out of scope in this thesis. Furthermore, based on discussions with industry experts, it was found that the decommissioning costs of mining energy project tend to be cost neutral - because decommissioning costs tend to be balanced out by the salvage value of the power system in mining projects (Engelhard, 2016). As a result, the decommissioning factor is neglected in this research and the following equation is used instead to calculate the annual investment costs at time t.

$$I = \alpha \cdot (C * \sum_{t=0}^{L_b} (1+i)^t) \tag{3.21}$$

The CRF (α) is determined by

$$\alpha = \frac{r}{1-(1-r)^{-L_T}} \tag{3.22}$$

Further details on financing assumptions and discount rates are provided in section 3.6.5 on page 63 with respect to financing mechanisms.

3.6.3 *Operation and maintenance costs*

The operation and maintenance costs (OM) are the sum of fixed costs (with respect to the system size) and the variable maintenance costs (which depend on both capacity factor and system size). Typically, the fixed costs are a proportion of the capital costs (without financing costs) and the variable costs are based on the actual operations represented by a cost per unit of energy output. It is worth noting that fuel costs are often included in this category of expenditure. In this research, a carbon tax is applied to some fuel costs in some scenarios, thus the fuel cost category is distinctively treated. The OM costs are calculated as follow:

$$OM = FC + VC \tag{3.23}$$

where FC represents the annual fixed costs, and VC are the annual variable costs - detailed cost estimates are given in data chapter 4 on page 91.

3.6.3.1 *Performance degradation*

The performance of most power technologies is likely to degrade over time, which might lead to power break-downs. This is particularly true for battery energy storage. Due to their chemical characteristics, a significant degradation of capacity takes place over time (i.e. more than 1% per year). Other technologies are also affected by performance degradation but at a lower scale.

In this research, the O&M costs were adjusted in order to take into consideration the most significant degradations of performance (i.e. battery energy storage). The calculation of the adjusted O&M costs OM_p is as follows:

$$OM_p = (FC + VC) + (I \cdot v) \tag{3.24}$$

where v is the annual degradation of performance for battery storage alternatives. It is therefore assumed that the degradation of performance is annually balanced out by new investments in additional capacities.

3.6.4 *Fuel costs*

3.6.4.1 *Annual fuel costs*

The annual fuel costs F are calculated as follow:

$$F = [CT + FC] \cdot \frac{E}{\eta} \tag{3.25}$$

Where the FC is the cost per unit of energy input, E is the annual energy output, η is the conversion efficiency, and CT is the carbon tax per unit of energy output. Two types of GHG emissions associated with fossil-fuel power can be distinguished (Moomaw et al., 2011): direct GHG emissions, and indirect GHG emissions related to the fuel lifecycle (e.g. infrastructure and supplies). Additional details on fuel prices and carbon emissions are provided in section 4.6.5 on page 104.

3.6.5 *Financing*

This section describes the financing hypotheses that have been applied to the economic analysis. First, the different financing alternatives are briefly discussed with regards to the chosen assumptions[2]. Second, the selected assumptions associated with taxation and uncertainty are provided. Third, the reasoning for the choice of the discount rate is described.

3.6.5.1 *Financing mechanisms*

Different capital structures can be applied to the project financing of hybrid renewable power systems. Historically, two main financing structures have been used for such projects (Slavin, 2014; Mendelsohn et al., 2012):

FLIP STRUCTURES In this financing structure, a third party (i.e. the developer) is in charge of planning, permitting, coordinating and building the project whereas the mining company operates as a tax equity investor - hence taking advantage of eligible tax incentives. An almost infinite number of models can be categorised in this structure. For instance, the "All-Equity Partnership Flip" is a model in which both the developer and the tax investor contribute a significant fraction of the required equity - using either project-level debt or equity financing - while the tax investor receives almost all the tax benefits. The cash benefits are distributed at different rates before and after the flip point - usually referred to as the IRR target year. Other common structures include the "Leveraged Partnership Flip" and the "Sale Leaseback" - which have different flip points, rates of cash distribution, and allocations of tax benefits.

IPP SINGLE-OWNER An "independent power producer" (IPP) model involves a single project owner which can either be the developer or a taxable company. One of these entities usually takes advantage of all the tax benefits associated with the project. The owner may use project-level debt or obtain equity financing. A PPA is usually signed with the developer when the mining company is not the project-owner[3]. A recent NREL report (Mendelsohn et al., 2012) has found that this structure provides the lowest LCOE

[2] Additional issues associated with financing mechanisms are discussed in section 8.4 on page 219

[3] It should be noted that there are numerous variations of this financing structure related to different sources of the equity financing (see section 8.4 on page 219).

costs in comparison to the most complex structures that involve flip points and multiple owners - mostly due to the lower interest rate applied in this model.

3.6.5.2 *Chosen mechanism and tax implications*

The scope of this research is the valuation of hybrid power systems in the context of an IPP single-owner financing structure. The most complex mechanisms (i.e. flip structures) provide economic incentives for renewable energy developers to promote such power systems but are unlikely to reduce the LCOE (Mendelsohn et al., 2012). Subsequently, these mechanisms are especially relevant to model the uptake of these systems - which is of interest for future research (as discussed in chapter 8 on page 213).

In terms of tax implications, the financial treatment of cash flows is linked to two main calculations: depreciation for tax purposes, and tax incentives. Depreciation enables a company to recover the cost of the power system through an income tax reduction. Even though all technologies are subject to depreciation, the timing of the tax reduction is different for operating costs and capital costs. In this respect, the fuel costs of fossil fuel plants can be recovered immediately whereas the capital costs of all technologies are recovered over the depreciation period. This period tends to be different for each type of technology. For instance, in the U.S., the recommended recovery period for hydro production plants is 20 years while it is only 15 years for combustion turbine production plants. Another key parameter is the depreciation method. Different tax rules can apply depending whether it is desirable to extend the depreciation period of the asset - even though shorter depreciation periods are preferred by most investors (Short et al., 2005).

In this research, the analysis was performed before-tax - hence neglecting the depreciation period and the income taxation. This type of analysis was selected in order to compare results across countries without being limited by country-specific tax policies. Yet, a number of specific tax incentives are discussed in section 8.4 on page 219.

A second implication is for potential tax incentives on low emission technologies. Historically, various mechanisms have been applied in order to lower emissions - i.e. Pigovian tax, trading schemes, or renewable energy tax credits on capital costs and production tax credit on energy output (see section 1.3.2.2 on page 8 and 8.4 on page 219 for further details). In order to facilitate the comparison of results across different countries, a simple Pigovian tax was used in HELiOS-Mining for a number of scenarios. Other taxation structures on emissions in mining remain of interest for future research.

3.6.6 *Discounting*

Discount rates are applied in economic calculations in order to take into account the time value of money and the risk inherent to an investment. The model HELiOS-Mining is based on real cash flows that exclude inflation. A real discount rate was therefore computed with the following formula:

$$r = [(1 + d_n) \; / \; (1 + e)] - 1 \tag{3.26}$$

where r is the real discount rate in the absence of inflation, d_n is the nominal discount rate, and e is the inflation rate. The inflation rate is set at 2.9% in this model - which is the historical average in the OECD for the CPI over the last 30 years (OECD-Stats, 2014). Discount rate values are typically dictated by industry standards based on the opportunity cost of capital. The value of this discount rate is discussed as follows.

ECONOMIC RETURN In the public sector, the discount rate is usually based on the risk-free Treasury bond rate. For instance, in the U.S, the recommended discount rate for renewable power generation is a real rate of 3% or a nominal rate of 6.6% (Petersen, 1993). In the private sector, there are no official guideline on the appropriate discount rate to apply in economic analyses. Most experts recommend to use a discount rate equal to the opportunity cost of capital (Short et al., 2005) - usually measured by the marginal cost of capital. Another similar metric is the Weighted Average Cost of Capital (WACC) which represents the average return that an entity has made on previous projects. It should be noted that the marginal cost of capital is usually preferred as it describes the opportunity cost for the next best project. However, investment decisions in mining projects are made on the basis of the economic return of the whole mine and not only the power costs. Hence the choice of the discount rate can be relatively different from one mine to another.

In this research, the discount rate was chosen on the basis of discussions with industry experts (Engelhard, 2016). Specifically, a central scenario of 12% (nominal) was selected while several different values were applied in the sensitivity analyses.

Alternatively, higher discount rates are often applied as an adjustment to capture the risk associated with a project. This practice is controversial and can be a poor substitute for a sensitivity analysis on input parameters. In this research, a number of sensitivity analyses were performed on input parameters - i.e. demand and costs parameters - while higher discount rates are considered in sensitivity analysis 5.3.2.1 on page 135.

3.7 RELIABILITY AND SYSTEM COSTS (RQ2)

In this research, the reliability evaluation of hybrid renewable power system is conducted by applying a cost to the power shortages as well as considering different climate scenarios. As a result, the optimal size of the reserve capacities is determined in relation to the least value of lost load and least system cost.

3.7.1 *Planned outages*

Some past authors have taken into consideration the planned outages by adding the capacity of maintenance to the load or subtracting it from the installed capacity (Billinton et al., 1996). A more precise approach is to determine the lost capacity of each unit on maintenance at each time step. While this is a better approach, a large number of assumptions need to be taken with regards to the time of maintenance and the scheduling of the mining activity.

In this research, it is assumed that the capacity associated with planned outages is subtracted from the rated power capacity as given by (Ibid):

$$y_{nk,a} = y_{nk} \times (1 - POR) \tag{3.27}$$

Where $y_{nk,a}$ is the power size of each technology nk with respect to the planned outage rate POR.

3.7.2 *Metrics*

Three reliability metrics have been applied to interpret the results associated with generation failure:

3.7.2.1 *Loss Of Load Probability (LOLP) and Loss Of Load Expectation (LOLE)*

Both indicators measure the probability of power shortages, the time-unit is hours for LOLP and days for LOLE - although some research use hours with LOLE (Allan and Billinton, 2000). The frequency of power shortages is given by (Yang et al., 2003):

$$LOLP = \frac{\sum_{i=1}^{n} hours(E_{S,h} < E_{L,h})}{n} \tag{3.28}$$

where $E_{L,h}$ is the electric load required by the industrial plant at hour h, $E_{L,h}$ is the electric generation by the hybrid system, and n is the number of hours for one year of operation. The weakness of this indicator is that it only determines the number of hours when power shortages take place; it does not provide information on shortage intensity, and times of power shortage.

3.7.2.2 *Loss of Energy Expectation (LOEE)*

This indicator measures the expected energy that will not be supplied at times when the load exceeds the available power. It encompasses both severity and likelihood of shortage. LOEE can be determined by (Allan and Billinton, 2000):

$$LOEE = \sum_{i=1}^{n} kWh(E_{S,h} < E_{L,h}) \tag{3.29}$$

3.7.2.3 *Energy Index of Reliability (EIR)*

EIR is derived from the LOEE to express reliability as a function of total system demand. Those ensure that large and small systems can be compared on the basis of a common index. The calculation is as follows (Allan and Billinton, 2000):

$$EIR = \frac{\sum_{i=1}^{n} kWh(E_{S,h} < E_{L,h})}{kWh} \tag{3.30}$$

3.7.3 *Reliability worth*

Previous studies have commonly applied Customer Damage Functions (CDF) and Customer Outage Cost (COC) to value power interruptions in relation to time of day, season, and various characteristics of a chosen industrial activity (for instance see Lawton et al. (2003) that reviews CDF for industrial activities). It is shown in section 3.9 on page 72 that the power demand associated with mining activities is relatively constant with very little variations associated with time of day and seasons (see 3.9.1.2 on page 73). Subsequently, it is assumed that the value of each unsupplied kWh is constant with no seasonal and temporal variations[4].

The value of lost load (VoLL) is used to represent the value that non-ferrous mines put on an unsupplied kWh, or in other words, the maximum cost a mine would be willing to pay to avoid an interruption (Kariuki and Allan, 1996). In this research, the VoLL is assessed based on the Value of Foregone Production (VFP) (Billinton et al., 1996). The VFP provides a value per kWh unsupplied as a function of the net revenue, as given by:

$$VFP = \frac{R_t}{E_{L,t}} \tag{3.31}$$

Where R_t is the net revenue in year t for a selected mine, and $E_{L,t}$ is the total electricity demand in year t (kWh) associated with the revenue R_t.

The total annual expected VoLL for the year t is given by:

$$VoLL_t = LOEE_t \times VFP_t \tag{3.32}$$

Note that the VFP could also be calculated by subtracting the Costs of Goods Sold (COGS) from the net revenue in order to eliminate the variable costs. This approach is not required in the mining industry for a number of reasons. First, the operating costs of mining companies mostly consist of fixed costs (i.e. depreciation charges) that remain constant if the activity stops. Second, the variable costs associated with labour are likely to remain constant for most power shortages - because the workers would remain at work until the power is back up. As a result, it is assumed that each kWh unsupplied is associated with a net loss of revenue that includes both fixed and variable costs.

A further assumption is that power break-downs have no financial impact on the valuation of mining assets. In other words, power shortages do not damage the mining equipment. This hypothesis was validated by mining experts in relation to the major mining processes of the non-ferrous metal industry (Engelhard, 2016) .

[4] Limitations for this assumption are discussed in section 6.2 on page 167

3.7.3.1 *Adequacy assessment*

The VoLL or inadequacy cost is the product of VFP and LOEE for outages when the system is not able to meet demand. The value of system inadequacy $VoLL$ for the year t can be determined by:

$$VoLL_t = LOEE_t \times VFP_t \tag{3.33}$$

3.8 PORTFOLIO APPROACH (RQ3)

3.8.1 *Mean-variance approach*

The standard portfolio model is applied to measure the outcome of a portfolio of generation technology with respect to the mean cost and standard deviation of costs (Jansen et al., 2006). This mean-variance approach is based on the average costs determined in research question one (as justified in section 7.1.1 on page 182) The solution with the minimum cost variance and the minimum expected cost is preferred. The applied methodology is provided below with five specific modelling steps.

In this research, the cost risk is considered to be the standard deviation of costs[5]. Hence this approach is used to assess the uncertainty associated with future fuel costs and a number of other factors such as different mine-life periods (i.e. investment period) and carbon taxation levels.

1^{st} : The unit cost of technology nk (UTCO) per unit of net output is calculated by summing-up the average unit costs of the cost categories i:

$$UTCO_{nk} = \sum_i C_{nk,i} = I_{nk,u} + VC_{nk,u} + FC_{nk,u} + F_{nk,u} \tag{3.34}$$

- where the cost categories i consist of $I_{nk,u}$ as the average investment cost for the technology nk, $VC_{nk,u}$ as the average variable cost, $FC_{nk,u}$ is the average fixed cost, and $F_{nk,u}$ is the average fuel cost. The cost of carbon emissions is here included in the fuel cost $FC_{nk,u}$ with respect to the carbon content of each selected fuel - see data section for assumptions on fuel costs in 7.1.1 on page 182.

[5]The semi-variance was also adopted for characterising the risk of shorter mine-life periods in section 7.3.2 on page 192.

- These cost components (index i) are expressed per unit of net output (kWh) - which is based on the average cost per unit discounted over the lifetime of the technology (or mine-life if shorter).
- The value of each component i for the technology nk is given by the following calculation (see previous section 3.4.0.1 on page 51 for definition of variables):

$$C_{nk,i} = \sum_{t=0}^{L_T} \frac{C_{nk,i,t}/(1+r)^t}{E_{nk,t}/(1+r)^t} \tag{3.35}$$

- Where $C_{nk,i,t}$ is the annual total cost of the cost category i.

2^{nd} : The average cost of portfolio p AC_p per unit of net output is given by taking into consideration the share of each technology in the portfolio (Delarue et al., 2011; Awerbuch and Berger, 2003), such as:

$$AC_p = \sum_{nk} X_{nk} \cdot UTCO_{nk} \tag{3.36}$$

- Where X_{nk} is the share of the technology nk (with respect to the net output) in the portfolio given by $X_{nk} = \sum_{t=0}^{L_T} \frac{E_{nk,t}}{\sum_{nk} E_{nk,t}}$
- Note that the value of the average cost AC_p is equal to the LCOE. In this respect, the calculation of the UTCO is a decomposition of the cost of each power plant included in the LCOE.

3^{rd} : The cost risk of each selected parameter FC^u_{nk} is calculated in order to determine the cost risk per technology:

$$\sigma_{nk} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (x_i - \mu)^2} \tag{3.37}$$

- With σ_{nk} is the standard deviation of the cost of the technology nk, x_i is the list of cost values for $FC_{nk,u}$, μ is the mean of all the value x_i, and N is the number of values in the list x_i.
- The value of σ_{nk} is considered to be the cost risk for a given power plant. This standard deviation is based on additional assumptions (e.g. normal distribution) that further discussed in section 7.2.1 on page 185.

4^{th} : The portfolio cost risk σ_p is given by:

$$\sigma_p = \sqrt{\sum_{nk}^{N} [X_{nk} \cdot \sigma_{nk}]^2 + \sum_{i=1}^{N} \sum_{k=1}^{N} 2 \cdot X_i \cdot X_k \cdot \sigma_i \cdot \sigma_k \cdot \rho_{ik}} \tag{3.38}$$

- Where i and k are two cost categories that present a correlation ρ. The second part of this equation is used to account for the correlation between fuel prices in systems that have two different fuels - hence considering the diversification effect of the portfolio theory, as detailed in section 7.2.2 on page 188.

5^{th} : The cost optimal portfolio is associated with the minimum average cost; and the risk optimal portfolio is associated the minimum standard deviation from the average cost. Both objectives are optimised together. Specifically, this approach is able to determine a number of non-inferior generation portfolios (i.e. Pareto optima), which results in a number of possible solutions.

$$J_{RQ3} = min\ F(x) \tag{3.39}$$

subject to:

$$F(x) = \left[AC_p, \sigma_p\right] \tag{3.40}$$

$$\sum_{nk} X_{nk} = 1 \tag{3.41}$$

$$X_{nk} \geq 0 \tag{3.42}$$

- Where F(x) is a vector of two objectives: AC_p is the average generation cost per unit of power for the portfolio p, and σ_p is the standard deviation of the average cost of the portfolio p.

3.8.2 *Selection of generation portfolios*

The different generation portfolios p are given by the optimisation model HELiOS-Mining based on optimal and near-optimal solutions. Near-optimal solutions include a number of technological combinations that are not part of the optimal solutions. The list of near-optimal solutions that are used as an input to the portfolio framework is given in 5.1 on page 114.

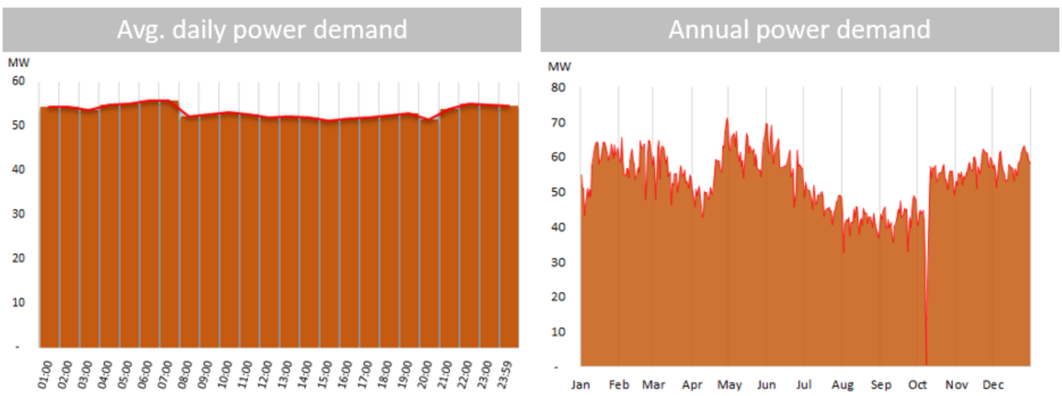
3.9 DEMAND: THE MINE LOAD

3.9.1 *Assumptions on energy demand*

This section describes the methods that were applied to model the mine load (i.e. power demand) in HELiOS-Mining.

Mining electricity load profiles have specific characteristics in terms of both long-term and short-term demand patterns. First, the short-term load profiles have been found to be relatively flat with limited intra-day variability (as shown in figure 3.2). The intra-day variability tends to be driven by the various maintenance processes - which can be classified as stochastic (i.e. condition-based and emergency maintenance). The maintenance of key machine tools in mining usually leads to the interruption of the whole manufacturing line - due to the continuous processes (Shahin et al., 2012). Subsequently, the short-term electricity demand of mining plants is characterised as predictable with an unpredictable component associated with unplanned maintenance and subsequent operation scheduling. This unpredictable component is inherently stochastic while the predictable component of the power demand can be classified as deterministic. Whereas a stochastic modelling of power demand was initially considered for this research, the computational requirements associated with stochastic processes were assessed to be too high for the optimisation model. Further considerations of stochastic power demand for different maintenance strategies remain of interest for future work (as stated in section 8.6 on page 222 on research limitations).

Figure 3.2: Daily and annual power demand of a copper mine (Spence - Atacama, Chile)



In terms of long-term power demand, it is assumed that the future power demand of a mine will be similar to the historical power demand. Hence, it is assumed that selected mines will continue “business as usual” for the remaining years of the mine-life. This assumption has implications in terms of maintenance strategy, manufacturing equipment (Shahin et al., 2012), and ore grade (Norgate and Jahanshahi, 2010). First, this assumption implies that the maintenance strategy of the chosen mines (e.g. time-based, condition-based, emergency maintenance) is to remain identical in future years. Second, this research assumes that selected mining plants will use similar machine tools in future years and neglects the degradation of efficiency of those machines. These two points are a limitation to this research as it is unknown whether a particular mine will change its maintenance strategy or manufacturing equipment in the future - which would both influence the short-term and long-term power demand (Li et al., 2011; Shahin et al., 2012). Third, this assumption implies that the variation of ore grades will not significantly change the overall power demand of selected mines. This limitation originates from the uncertainty associated with ore grades and mining strategy. For instance, mining companies can decide to refine low grade ore at times when the price of the commodity reaches a minimum threshold - which is inherently unknown. Ultimately, while a number of scenarios on ore grade and energy demand could be modelled, this area is out of the scope of this research but is carefully discussed in section 8.2 on page 214.

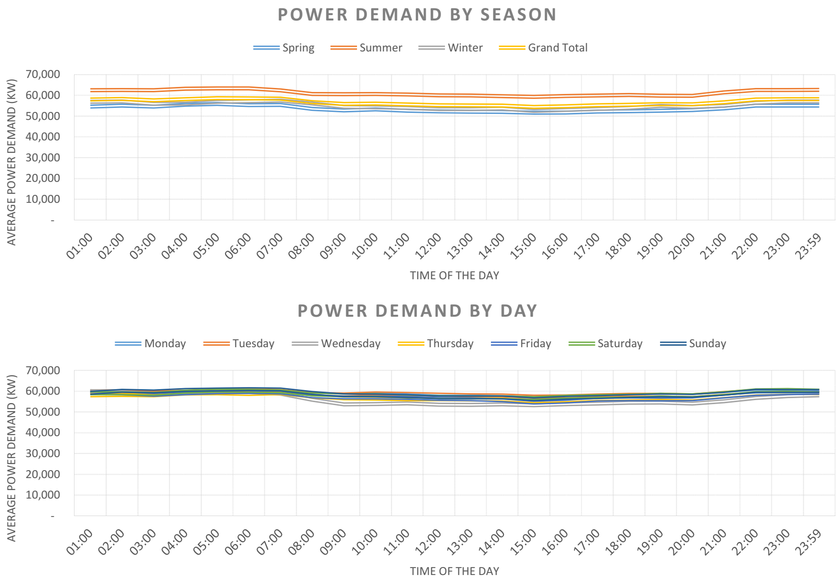
3.9.1.1 *Historical power demand*

Historical data are a major input to HELiOS-Mining for all three research questions. The data sources associated with the historical power demand include the hourly power demand for two to three years of operation. This power demand is provided at an aggregated level which includes all mining processes. The latest year from the historical energy demand dataset was used in HELiOS-Mining. Further information and download links associated with various data sources are provided in the data chapter (see 4.2 on page 92). A different method was applied for modelling the power demand of new mines - for which there are no existing data; as detailed in section 3.9.1.3 on the following page.

3.9.1.2 *Seasonal variability of power demand*

Historical data suggest that there are no specific patterns of seasonality between weekday/weekends, summer/winter, or by day of the week. Figure 3.3 shows this phenomenon for a selected mine. Interestingly, this was found to be true for in all mines present in the dataset of this research - and confirmed by several mining experts (Engelhard, 2016).

Figure 3.3: Seasonal and daily variations of the power demand



3.9.1.3 *Data extrapolation to other mines*

While it is possible to collect data for existing mines, the power demand of new mines needs to be modelled. Both existing and new mines are analysed in this research.

In this context, the projected power demand was modelled on the basis of the load profiles of existing mines. Specifically, the data of a similar mine was chosen for calculating the expected power demand of a new mine. The choice of the similar mine was made based on several key factors. First, past authors have determined that the ore grade is one of the most important component for mining power demand (Norgate and Jahanshahi, 2010). This component is associated with the amount of energy required to liberate the metal from the ore. The finer the ore, the higher the energy need (Pitt and Wadsworth, 1980). Second, another important determinant of energy demand in mining is the type of process that is used in the refinement of the ore. For instance, two main types of furnaces can be used for smelting: reverberatory furnace and flash furnaces. The first one uses fossil-fuel and the second one uses electricity. Finally, the type of finished product can be different for the same ore. For instance, a copper mine can either produce copper concentrate (30-40% copper content) or copper cathode (99.99% copper content) - hence encompassing different levels of energy demand.

Ultimately, all these criteria have been used to select an appropriate set of data for a given mine. The selection of the appropriate dataset is further detailed in the data chapter. Using the historical data of a similar mine, the power demand of new mines was determined by a linear extrapolation based on the expected peak power demand given in the feasibility studies that are published for new mines. Further details on selected mines are provided in the data chapter 4 on page 91.

3.9.2 *Demand-shifting assumptions*

This section describes the applied methodology for simulating the impact of shifting power demand from one time to another. While this is an area of interest for future research, the matter of demand-shifting is not one of the primary objective of this research and is therefore tackled with a scenario-based perspective (rather than a detailed engineering analysis). In this context, the assumptions associated with demand shifting are determined on the basis of previous research and a number of potential scenarios.

A few past papers have provided theoretical assumptions associated with power demand-shifting for the mining industry. Paulus and Borggrefe (2011) have provided some estimates for five industrial process. They found that 25% of the power demand of the aluminium electrolysis can be reduced by up to 25% for 4 hours. Middelberg et al. (2009) have proposed a time-shifting model for the conveyor belts of a South African coal mine. They stated that an optimal time scheduling of the conveyor belt operation could reduce the total amount of energy during peak time from 25% to 8% - and therefore reduce energy costs by up to 49%.

In this research, a number of assumptions were tested with regard to the amount of power demand that can be shifted in section 5.3.2.2 on page 137. This method was adapted from traditional DSM methods applied to residential customers (Paatero and Lund, 2006).

Specifically, the following assumptions were used for time-shifting the power demand of a mining plant:

- Demand-shifting is only allowed to happen at times where the renewable power plants are providing extra power capacity (i.e. renewable generation is higher than the power demand). In these cases, the model is allowed to shift demand from previous and following hours to the current hour (the number of hours that can be shifted is different for each scenario);
- Demand-shifting has priority over storage charging. It is therefore assumed that demand-shifting provides a better economic value than storage capacity;

- Finally, the mining plant has an oversized system that is capable of processing more ore at times when the demand is shifted (the amount of processing capabilities is different for each scenario).

3.10 SUPPLY: THE POWER SYSTEM

This section describes the various components of HELiOS-Mining associated with power supply. First, the selected storage strategy is detailed with respect to various business models. Second, the applied methodologies for each selected technology are then provided.

3.10.1 *Storage strategy*

The supply of power to mining activities can be accomplished differently depending on the context (i.e. grid connection, remoteness, load profile) and the objectives of the selected mine (Boyse et al., 2014). An appropriate business model has to be chosen accordingly - which encompasses specific storage strategies. Relevant storage strategies in relation to each business model are briefly described below. In the last paragraph of this section, the selected storage strategies for this research are provided.

SELF-GENERATION MODEL (OFF-GRID) This model is relevant for a single mine that is not connected to the grid and relies entirely on local generators for electricity. In this scenario, the local power system is solely responsible for power reliability. The relevant storage strategies for this business model are associated with off-peak strategies: dispatchable renewables (i.e. renewables and storage) and hybrid systems (i.e. fossil-fuel, renewables, and storage).

NET-METERING (GRID-CONNECTED) This model assumes that the mine is connected to the grid, from which it purchases power. In this strategy, it is assumed that the grid is fully flexible to deal with any intermittency of renewable generation. Based on expert opinions, a net-metering strategy might be difficult to implement in some mining regions due to intermittency challenges (Engelhard, 2016). For instance, in the Chilean Atacama region, the load profile of the grid is relatively flat as most of the power is sold to mining companies. As a result, the power efficiency of the local utility would probably decrease if mining companies were to purchase power in an inconsistent manner.

Three additional storage strategies can be derived from the net-metering model: peak load management, baseload renewables, and capacity firming. The first strategy (i.e. peak load management) may not be compatible with mining activities as electricity is usually sold at a fixed price to mining companies under a PPA agreement (Ibid). The second strategy is based on a system that supplies a constant electricity output. While this strategy is relevant to some renewable alternatives such as biomass or geothermal, it is relatively difficult to implement for the most unpredictable options (i.e. wind, solar). Finally, the third strategy aims at guaranteeing a minimum output from the hybrid renewable power system. Above this output threshold, the intermittency is managed by the grid.

self-generation + powering townships model (off-grid) This model applies to off-grid mines that are solely relying on local generators for their electricity consumption and are also powering neighbourhood communities. All off-peak storage strategies can be applied in this business model, but dispatchable systems (i.e. without fossil-fuel resources) might provide additional benefits in this context - as the heterogeneity of load profiles can help managing intermittency.

industrial pooling model (off-grid) This model assumes that several industrial actors - all unconnected to the grid - are pooling resources to reduce power costs. Whereas this model can seem attractive, negotiating such structure would be challenging. Given the uncertain lifetimes of neighbouring projects, and potentially divergent interests, mining companies have shown little interest in undertaking joint capital projects with their competitors (Boyse et al., 2014). Yet, it would be interesting to economically assess this model in future research.

3.10.1.1 *Research scope: selected business models*

In this research, the first two business models (i.e. self-generation and net-metering) have been modelled in section 5.3.1.3 on page 130. Each model encompasses different implications for the power system. In particular, the self-generation model must rely on large amounts of energy storage (or fuel-based capacity) in order to manage the intermittency of renewable technologies. As for the second model, the net-metering and the capacity firming options have been selected as the most appropriate strategies for powering mining activities.

As a result, the research model HELiOS-Mining is based on three different strategies associated with different grid involvements:

- Self-generation: off-grid stand-alone power system,
- Capacity firming: partial management of renewable intermittency by the grid - above a minimum guaranteed output,
- Net-metering: full management of renewable intermittency by the grid.

Algorithms and calculation details associated with these strategies are provided in the following section.

3.10.2 *Storage: Technical parameters*

3.10.2.1 *Selected storage technologies*

Two key storage technologies were selected for this research based on technological maturity and discussions with mining experts: Li-Ion battery and molten-salt thermal storage (as detailed in section 4.4 on page 95). These storage alternatives are technologically mature and can be deployed at the scale required for mining activities.

MATHEMATICAL FORMULATION OF CHARGING AND DISCHARGING CYCLES The storage system is sized by the optimisation algorithm in relation to the storage strategy (as detailed previously) as well as the technical and economic characteristics provided in the methodology and data chapters (see objective function 1 in section 3.4 on page 51).

The difference between renewable power output and electricity demand determines when to charge or discharge the storage system. It is therefore assumed that the storage system is only charged by residual renewable power output.

The charge quantity of the storage system at time h is given by (Ai et al., 2003):

$$E_{St_k,c}(h) = E_{St,k}(h-1) + (E_R(h) - E_L(h)/\eta_{inv})\eta_{St_k} \tag{3.43}$$

The discharge quantity of the storage system at time h is determined by:

$$E_{St_k,d}(h) = E_{St,k}(h-1) - (E_L(h)/\eta_{inv} - E_R(h))\eta_{St_k} \tag{3.44}$$

where $E_{St_k,c,d}$ is the charging/discharging energy into the storage system St_k in the hour h, E_R is the net amount of energy generated by the renewable power system (i.e. wind, solar), $E_L$is the power demand, η_{inv} is the efficiency of the power conditioning unit, and η_{St_k} is the efficiency of the charging or discharging cycle (as opposed the efficiency of the full cycle).

Both cycles are subject to a number of constrains:

$$E_{Stmin} \leq E_{St_k,c,d}(h) \leq E_{Stmax} \tag{3.45}$$

$$E_{St_k,c,d}(h) \leq E_{Stpow} \tag{3.46}$$

where E_{Stmin} is defined by the maximum depth of discharge (DOD), E_{Stmax} is the nominal capacity of the storage device, and E_{Stpow} is the maximum power discharge of the storage device (hourly). The initial storage capacity (i.e. in the first hour of the simulation) is set to half of the total storage capacity. Note that storage efficiencies and costs are given in the data chapter for each storage technology in sub-sections 4.6 on page 101 and 4.5 on page 96.

STORAGE ALGORITHM The mathematical formulation of the charging and discharging cycles was rewritten in an algorithmic form in order to model the storage constrains (i.e. DOD, size of power electronics, storage capacity) in HELiOS-Mining. The algorithms 3.1 on the following page, 3.2 on page 81, and 3.2 on page 81 provide the details of the hourly steps that are followed in order to calculate the amount of storage charging, discharging, and the hourly balance. This process is followed for each of the 8760 hours modelled in HELiOS-Mining. A number of explanatory comments on objectives, definition of variables, and resulting outputs have been added in the appropriate sections of the algorithm.

Algorithm 3.1 Hourly storage charging in HELiOS-Mining (Python code)

```
1  #1) CHARGING algorithm: Returns the hourly amount of power (before losses) that is charged to the storage system for each hour of the simulation
2  @xl_func("int Stpwr, int StCap, int Stlvl,int RenGen, int PwrDmd, float Stloss1way")
3  def CHARGING(Stpwr, StCap, Stlvl, RenGen, PwrDmd, Stloss1way):
4  #DEFINITIONS of the variables:
5      #Stpwr: Maximum gross amount of power (kW) that can be charged/discharged per hour (i.e. size of the power electronics)
6      #StCap: Maximum gross amount of power capacity (kWh) that can be charged/discharged over a number of hours (i.e. size of the storage capacity)
7      #Stlvl: Current amount of power capacity available for discharge (kWh)
8      #RenGen: Current amount of power generation from renewable sources (kW)
9      #PwrDmd: Current amount of power demand from the mine (kW)
10     #Stloss1way: Net efficiency after accounting for storage losses associated with either the charging or discharging cycle (%)
11     if Stlvl < StCap:
12         if (RenGen - PwrDmd)>0:
13             if (Stlvl + RenGen - PwrDmd) < StCap:
14                 if RenGen - PwrDmd < Stpwr:
15                     return (RenGen - PwrDmd)
16                 else:
17                     return Stpwr
18             else:
19                 if (StCap - Stlvl) / Stloss1way < Stpwr:
20                     return (StCap - Stlvl) / Stloss1way
21                 else:
22                     return Stpwr
23 #CONSTRAINTS: This algorithm performs a number of checks:
24     #availability of storage capacity as a function of the storage level (line 11),
25     #residual amount of renewable power supply (line 12),
26     #available amount of storage capacity in kWh (line 13 and 19),
27     #available amount of power capacity in kW (line 14).
28 #RESULT: Returns the appropriate amount (gross) of renewable power that can be charged into the storage system (line 15, 16, 20, and 22).
```

Algorithm 3.2 Hourly storage discharging in HELiOS-Mining (Python code)

```
1  #2) DISCHARGING algorithm: Returns the hourly amount of power (before losses) that
       is discharged from the storage system for each hour of the simulation
2  @xl_func("int Stpwr, int StCap, int Stlvl, int RenGen, int PwrDmd, float Stloss1way
       , float DoD")
3  def DISCHARGING(Stpwr, StCap, Stlvl, RenGen, PwrDmd, Stloss1way, DoD):
4      OutputNeeded = (PwrDmd - RenGen) / Stloss1way
5      StlvlAvail = Stlvl - StCap * (1 - DoD)
6  #DEFINITIONS of the variables:
7      #DoD: Value of the maximum Depth of Discharge (DoD) for a chosen storage device
            (between 0 and 1; 1 being the full capacity)
8      #OutputNeeded: Required amount of net discharge to cover the full residual
           power demand (kW)
9      #StlvlAvail: Amount of storage capacity available for discharge during the
           present hour (kWh)
10     if StlvlAvail > 0:
11         if PwrDmd > RenGen:
12             if StlvlAvail > OutputNeeded:
13                 if OutputNeeded < Stpwr:
14                     return OutputNeeded
15                 else:
16                     return Stpwr
17             else:
18                 if StlvlAvail < Stpwr:
19                     return StlvlAvail
20                 else:
21                     return Stpwr
22 #CONSTRAINTS: This algorithm performs a number of checks:
23     #availability of storage capacity as a function of the storage level (line 10),
24     #residual amount of power demand that is not covered by the renewable
           generation plants in kW (line 11),
25     #available amount of storage capacity in kWh (line 12),
26     #available amount of power capacity in kW (line 13 and 18).
27 #RESULT: Depending on the value of these checks, the algorithm returns the
       appropriate amount (gross) of power that is discharged to meet the residual
       demand (line 14, 16, 19, and 21).
```

Algorithm 3.3 Hourly balance of storage in HELiOS-Mining (Python code)

```
1  #3) BALANCING function
2  @xl_func("int Stlvl, int StCharging, int StDischarging, float Stloss1way")
3  def BALANCE(Stlvlph, StCharging, StDischarging, Stloss1way):
4  #DEFINITIONS of the variables:
5      #Stlvlph: Amount of storage available at the beginning of the previous hour (
           kWh)
6      #StCharging: Gross amount of power that was charged on the storage system
           during the previous hour (kWh)
7      #StDischarging: Gross amount of power that was dicharged from the storage
           system during the previous hour (kWh)
8
9      Stlvl = Stlvlph + (StCharging * Stloss1way) - StDischarging
10
11 #RESULT: Determine the net amount of kWh that is available for the current hour in
       relation to the previous discharge or charge (after accounting for losses)
```

3.10.3 *Renewable power generation*

3.10.3.1 *Selected renewable technologies*

A number of renewable technologies have been modelled in this research. The choice of in-scope technologies was made on the basis of numerous discussions between mining experts and the industrial sponsor of this PhD. As a result, the selected renewable technologies in this thesis include: wind power, solar PV (tilted and tracking), CSP with parabolic trough, and CSP tower (also see section 4.4 on page 95 for further details on the selection of technologies). The applied methodology to model each renewable alternative is provided as follows. Note that Biofuel power generation was also considered (see section 3.10.4.3 on page 87 on diesel power generation). The potential to use Biofuels is also discussed in section 8.6 on page 222.

3.10.3.2 *Wind*

The power output of a wind turbine is associated with both wind speed at hub height and speed characteristics of the turbine.

Wind speed at hub height is given by applying the power-law equation, or Hellman exponent (Patel, 2005)

$$V_z = V_i \left[\frac{Z}{Z_i} \right]^x \tag{3.47}$$

where V_z is the wind speed at hub height, V_i is the wind speed at reference height, Z is the hub height, Z_i is the reference height, and x is the power-law exponent (or hellman exponent) that depends upon the coastal location, the shape of the terrain on the ground, and the stability of the air. Examples of this exponent for different configurations are given in table 3.1 while selected Hellman exponents for this thesis are provided in the data chapter 4 on page 91.

Power output per square meter from wind turbine generator is be given by (Deshmukh and Deshmukh, 2008; Kaltschmitt et al., 2007)

$$\begin{aligned} P_{w,m2} &= 0, & V_z &< V_{ci}, \\ P_{w,m2} &= aV^3 - bP_r, & V_{ci} &< V_z < V_r, \\ P_{w,m2} &= P_r, & V_r &< V_z < V_{co}, \\ P_{w,m2} &= 0, & V_z &> V_{co}, \end{aligned} \tag{3.48}$$

where V_{ci}, V_{co}, V_r, are the cut-in, cut-out and rated speed of the wind turbine, $a = P_r/(V_r^3 - V_{ci}^3)$, and $b = V_{ci}^3/(V_r^3 - V_{ci}^3)$.

Actual power output $E_{W_k,h}$ from wind turbine k at hour h is determined by

$$E_{W_k,h} = P_{W,m2} * A_W * \eta_W \tag{3.49}$$

where A_w is the total swept area, η_w is the efficiency of the wind turbine generator including power conditioning.

Table 3.1: Hellman exponents (Kaltschmitt et al., 2007)

location	x
Unstable air above open water surface	0.06
Neutral air above open water surface	0.10
Unstable air above flat open coast	0.11
Neutral air above flat open coast	0.16
Stable air above open water surface	0.27
Unstable air above human inhabited areas	0.27
Neutral air above human inhabited areas	0.34
Stable air above flat open coast	0.40
Stable air above human inhabited areas	0.60

3.10.3.3 *Solar: Photovoltaic panels*

The hourly solar power $E_{S,PV}$ produced by a photovoltaic array with an area A_{PV} during the hour h at the total solar irradiation S (for a given incline) is calculated by (Habib et al., 1999):

$$E_{S_{PV},h} = S_h * \eta_{PV} * A_{PV} \tag{3.50}$$

where the total system efficiency η_{PV} is determined by

$$\eta_{PV} = \eta_m \cdot \eta_{pc} \tag{3.51}$$

where η_m is the module efficiency and η_{pc} is the inverter efficiency.

The different data-sources associated with solar data at different azimuths and tilts are provided in the data chapter in section 4.3 on page 94.

3.10.3.4 *Solar: Concentrated Solar Power*

Three different CSP technologies are currently available: parabolic dish, power tower, and parabolic trough. The parabolic trough is the most mature technology and the easiest to maintain while the power tower configuration has recently gained interest from the mining industry - due to higher operating temperatures and higher conversion efficiencies. For these reasons, both parabolic trough and power tower have been modelled in this research. It is assumed that CSP is used to produce electricity - as opposed to heat output - as this is the focus of this research (potential for heat output is discussed in section 8.6 on page 222).

A concentrated power plant includes three main components: the solar field, the power block (i.e. steam turbine), and thermal storage. As a result, a CSP plant can be used to directly power the mining operation or store thermal energy for later use.

The chosen method for modelling CSP output is given by Zhang et al. (2010). This method allows a dynamic representation of CSP plants that can be included in an economic analysis. The following equation is used to determine the output $E_{S_{CSP},h}$ of the CSP plant in hour h:

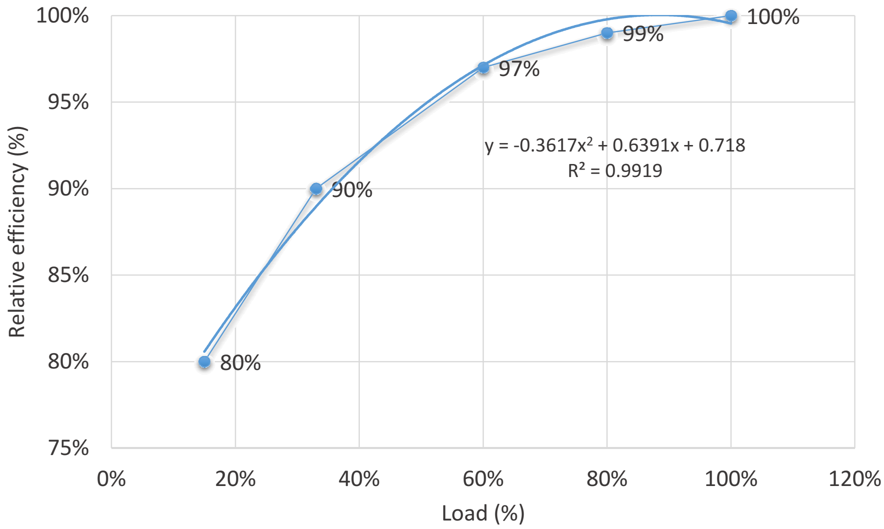
$$E_{S_{CSP},h} = \eta_{turbine} Asf(DNI_{\varepsilon opt} - Loss_{HCE} - Loss_{SFP}) \tag{3.52}$$

where $\eta_{turbine}$ is the turbine gross efficiency, Asf is the collecting area of the CSP field, $DNI_{\varepsilon opt}$ is the optimal efficiency of the CSP plant associated with the Direct Normal Irradiance (DNI), $Loss_{HCE}$ is the thermal loss of the heat collector, $Loss_{SFP}$ is the heat losses from field pipes. The parasitic losses associated with start-up energy have been neglected in this research - as their impact have little significance on the total power output.

The ramp rate of the steam turbine was evaluated to be around 10% of the capacity per minute (Jorgenson et al., 2013) - therefore the full load can be obtained after 10 minutes. Because this model is based on the hourly balance of power demand and power supply, this parameter has been neglected in the modelling process - see discussion section 8.6 on page 222.

Finally, the power output of the steam turbine has to be characterised in relation to the storage output and the rated capacity. In other words, if the storage output is below the rated capacity of the power block, the ratio of relative heat input is higher than 1 - therefore decreasing the overall efficiency of the storage system. The heat ratios used in this research are given by Jorgenson et al. (2013) - as illustrated in figure 3.4. Based on these data, a second order polynomial regression was performed to determine the efficiency as a function of the load factor - as provided on the figure 3.4. This function was used to determine the relative efficiency of the CSP power block (i.e. steam turbine).

Figure 3.4: Relative efficiency of the CSP power block



Both CSP technologies (i.e. parabolic trough and power tower) can be modelled with the same methodology (Jorgenson et al., 2013). Yet, it should be noted that the value of $DNI_{\varepsilon opt}$ is different for parabolic trough and power tower. The value of the former being the DNI for single-axis tracking while it is the DNI for double-axis tracking on the latter.

An interesting aspect of the CSP technology is the ability to use a natural-gas-fired boiler that generates steam to run the turbine. This can be an attractive feature to provide backup power when the thermal storage is empty. However, the efficiency of such technology is usually significantly lower than conventional stand-alone gas turbine (i.e. high parasitic losses). Zhang et al. (2010) suggests that the gas-to-electricity conversion efficiency is assumed to be 32% in CSP systems. The applied methodology to calculate the output of the CSP gas-backup boiler is identical to the methodology associated with natural gas power generation - see 3.10.4.4 on page 89.

STORAGE COMPONENT The storage component of the CSP plant follows the same algorithm of charge and discharge cycles detailed in 3.10.2 on page 78. The efficiency of thermal storage is more sensitive to decay losses than other storage technologies.

Whereas a traditional battery storage (e.g. Li-Ion) would lose an insignificant amount of energy overnight, a CSP thermal storage will suffer significant heat losses over time. The focus of this research is on short term storage (as opposed for instance to seasonal storage), therefore this model is designed around a full cycle of charge/discharge per day. In this context, it is reasonable to assume a fixed rate for decay losses (see table 4.3 on page 98).

3.10.4 *Fossil fuel power generation*

3.10.4.1 *Selected technologies*

In this research, the most relevant fossil-fuel technologies for mining activities have been modelled, including diesel and natural gas power generation. Whereas this research has a strong focus on renewable power generation and energy storage, conventional power alternatives using fossil-fuel can be used to complement those technologies and minimise system costs. Grid power supply is also considered as part of this category. The applied methods to model each of these alternatives are provided as follow.

3.10.4.2 *Energy output of fuel-based technologies*

Fuel-based technologies are dispatched in relation to the output of non-dispatchable technologies as well as energy storage output, as given by the equation 3.53:

$$E_{FF_k,h} = E_{L,h} - \left[E_{W_k,h} + E_{S_k,h} + E_{St_k,h}\right] \tag{3.53}$$

Where the energy storage output $E_{St_k,h}$ is defined in section 3.10.2 on page 78.

3.10.4.3 *Diesel*

Diesel power generation is considered in this research as part of a hybrid power system including both renewable/storage and conventional fossil-fuel based technologies. The fuel consumption and the operational efficiency are modelled based on external conditions, power losses, and loading factors. The net efficiency of the genset η_D is given by:

$$\eta_D = \left[\frac{\eta_D(l/h) * LHV_f}{P_D} \right] * LF \tag{3.54}$$

where $\eta_D(l/h)$ is the fuel consumption at full load, LHV is the lower heating value of the fuel f (diesel is assumed to be 11.55 kWh/l), P_D is the nominal power output of the genset, and LF are the relative efficiencies associated with part-loading. The following coefficients were applied to take into consideration that the load is not always equal to the rated power output - hence reducing the efficiency of the generator. Specifically, the following assumptions were applied for part-loading (Engelhard, 2016):

- 25% of the total power output is at full rated load
- 50% of the total power output is at medium load resulting in a decreased efficiency of 2%
- 25% of the total power output is at minimal load resulting in a decreased efficiency of 6%

It is assumed that the management of the entire diesel plant is performed by turning on/off the different diesel modules in order to reach these part-load efficiencies. Consequently, the load factor coefficient is given by:

$$LF = (0.25 * 1) + (0.50 * 0.98) + (0.25 * 0.94) = 98\% \tag{3.55}$$

An alternative methodology would be model the precise variation of efficiency as a function of the power output (Dufo-Lopez and Bernal-Agustin, 2008). Yet, this method is not adequate for HELiOS-Mining as it would require to model the diesel power at the module level and not at the system level. Subsequently, this research takes the assumption that the derating coefficients (given previously) for part-loading are able to capture the overall operational efficiency of the entire diesel plant - which consists of a number of individual generators. This assumption was validated by a major manufacturer of diesel plants (Engelhard, 2016).

The fuel cost per kWh of the genset FC_D is calculated as follow:

$$FC_D = DP_l / LHV / \eta_D \tag{3.56}$$

where DP_l is the cost of diesel fuel (per litre) for the selected mine including transportation costs.

Note on the sizing of diesel generators It should be made clear that the sizing of diesel generator is not only based on the power demand at the mine site (Mahon, 1992). Specifically, the following characteristics were taken into consideration in the simulation and optimisation process:

- No consideration of diesel overload: In practice, the gensets can run at 10% above the prime rating for 1 hour every 24 hours.
- Ambient conditions: a number of derating coefficients were also applied in order to take into account the elevation and the external temperature at mine site (see table 3.2). These coefficients indicate that the genset size might need to be oversized in relation to ambient conditions. Relative humidity has only a minor impact and is neglected in HELiOS-Mining (Kehlhofer et al., 2009).

Table 3.2: Derating factors associated with the external conditions (DR_C) of diesel generators

Avg. temperature (DR_t)		**Altitude (DR_A)**	
35°C	0.99	150m	0.99
40°C	0.98	250m	0.98
45°C	0.97	350m	0.97
50°C	0.96	450m	0.96
		500m	0.95
		550m	0.94
		600m	0.93
		650m	0.92
		700m	0.91
		750m	0.9
		800m	0.89
		850m	0.88
		900m	0.87
		950m	0.86
		1000m	0.85

Finally, the given power sizes in this research are based on prime power and not standby power. The standby power rating is typically 10% higher than the prime power but can only be used in case of emergency.

3.10.4.4 *Natural gas*

Power generation plants using natural gas or LNG are considered in this research with respect to conventional gas turbine (GT) and combined cycle gas turbine (CCGT). LNG power generation is being increasingly considered for remote mines (i.e. trucked LNG) for replacing diesel fuel and is therefore of interest in this research.

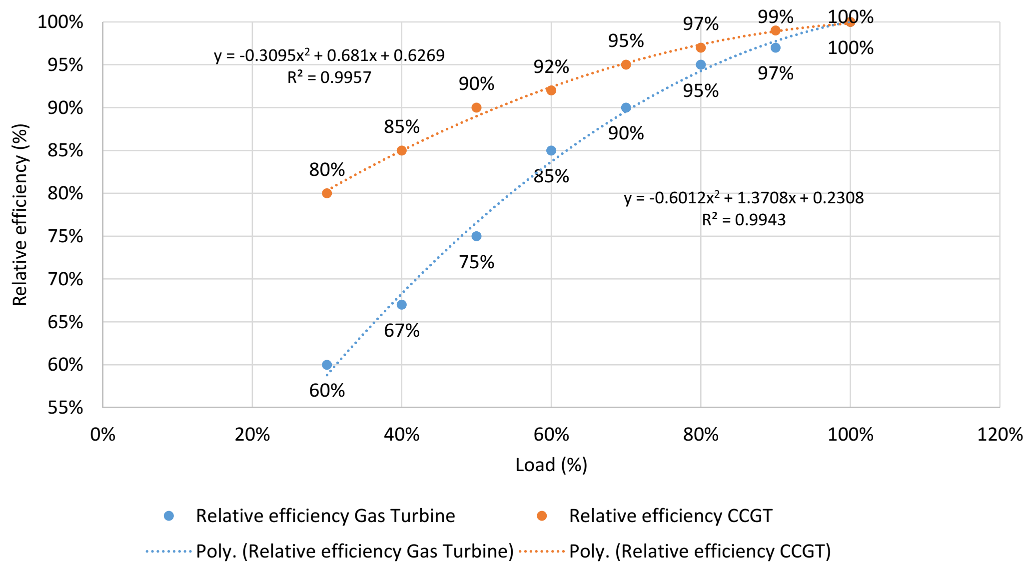
The fuel cost per kWh at hour h of the natural gas plant FC_G is calculated as follow (Kehlhofer et al., 2009):

$$FC_{G,h} = \frac{3.142 \times GP_{MMBTU,t}}{\eta_{G,h}} / 1000 \tag{3.57}$$

Where the numerator expresses the price in US$/MWh thermal, GP_{MBTU} is the cost of natural gas in US$/MMBTU for a chosen mine in year t - including transportation costs, and η_G is the operating efficiency of the turbine for the hour h.

The relative efficiency of the plant $\eta_{G,h}$ takes a different value for different capacity factors - as given by (Kehlhofer et al., 2009). The figure 3.5 provides these values for both gas turbine and CCGT alternatives. Two second order polynomial regressions were computed to determine the value of the relative efficiency as a function of the load - which were found significant at the 1% level. As a result, the relative efficiency of the plant is determined hour by hour in HELiOS-Mining for each unit. Both equations are provided in figure 3.5.

Figure 3.5: Relative efficiency of gas turbine and combined cycle



Finally, a number of derating coefficients were also applied in order to take into consideration the ambient conditions. Table 3.2 on page 88 provides these coefficients for different elevations and external temperatures.

3.10.4.5 *Grid connection*

In this research, it is assumed that the grid power can be used to fully complement the local power system (i.e. net-metering strategy) or to partially complement the local system by providing power above a minimum guaranteed output from the on-site power system (i.e. capacity firming strategy). A third alternative can also be envisaged when the grid power is too expensive in comparison to off-grid costs. In this case, the self-generation strategy can be implemented in order to meet the power demand of the mine through an off-grid power system (as reviewed in section 3.10.2 on page 78). Grid-extension alternatives are discussed in section 8.6 on page 222.

4

DATA

The data chapter is used to describe the data sources, cost estimates, and technical parameters that were used in HELiOS-Mining as well as to provide some background on selected mines. Key selection criteria for the mines that were investigated in this thesis are subsequently given in section 4.1. Selected mines and their key characteristics are detailed in section 4.2 on the following page. Sources of chosen datasets for climate data are provided in section 4.3 on page 94. Finally, a summary of technical parameters is provided in section 4.5 on page 96 whereas a summary of cost estimates is given in section 4.6 on page 101.

4.1 MINE SELECTION

A number of mines have been selected for this research based on the following criteria:

- Representativeness of major mining regions: The selection of major mining regions provides the opportunity to generate insights that can be generalised to neighbouring mines (given that the power demand is based on a continuous processes).
- Renewable resource availability and diversity: This study aims at representing different renewable technologies, which implies that different types of climate have to be considered. Furthermore, mining regions with off-grid mines are preferred given the cost advantage of renewable alternatives compared to grid-connected mines (i.e. high diesel power costs for off-grid systems).
- Mining activity: This thesis focuses on non-ferrous metals. Non-ferrous metal mining and processing are based on the use of continuous processes and 61% of the energy demand for these processes is electricity.

Accordingly, the mine selection was performed on the basis of these three criteria.

In terms of representativeness of major mining regions, the Investment Attractiveness Index (Jackson and Green, 2015) was used to determine the mining areas that present the most attractive characteristics for mining activities with respect to 15 factors, e.g. policy, economic, infrastructure, political stability, or availability of skilled labour[1]. This index ranked Canada, U.S.A, and Australia as the most attractive countries on a global scale for mining activities. Chile was assessed to be the best ranking country of Latin America with a score of 80 over 100. Finally, Ireland has been assessed to be the most attractive mining in Europe (average score of 82 over 100).

In terms of resource availability, Canada and Ireland would be both good candidates for wind power alternatives but Canada presents a greater potential for off-grid systems (i.e. remoteness). Chile and Australia are good candidates for both solar and wind alternatives, for both off-grid and grid connected mines. U.S.A. presents significant renewable potential, yet most mines are grid-connected.

As for mining activities, non-ferrous metals are the main focus of mines located in Canada, Australia, and Chile. In Canada, there are currently 83 gold mines in operation and 18 copper mines - and a total of 82 active mines of non-ferrous metals. In Chile, there are 73 operating copper mines and a total of 89 non-ferrous mines. In Australia, there are 148 operating mines for non-ferrous metals with 83 operating gold mines and 18 copper mines. Together, these three countries possess one third of the global copper mines and present the highest number of copper mining projects, i.e. advanced exploration and feasibility phases (SNL, 2016).

As a result, three countries have been identified for this research, namely Canada, Chile, and Australia. All three countries are major mining regions that possess diverse sources of renewable energy while having significant non-ferrous metal resources.

4.2 SELECTED MINES

Given previous-mentioned criteria, three distinct mines have been selected for this research, including Spence mine in Chile, Casino project mine in Yukon (Canada), and DeGrussa-Sandfire in Australia. Together, these mines fit the selection criteria on climate diversity, representativeness of major mining regions, and mining activity[2].

[1] It should be noted that the resulting index measures mining attractiveness and not mining intensity. Yet, because mining companies are highly likely to invest more intensively in the most attractive countries, this index is deemed to be an adequate proxy to identify major mining regions.

[2] Note that the findings associated with these mines are partially generalisable to the neighbouring mines of selected mining regions - see section 8.7 on page 226.

A description of selected mines is provided as follows and a summary of the characteristics of each mine is given in table 4.1.

Table 4.1: Key characteristics and assumptions for selected mines

Name	Location	Mined Resources	Mine Life	Mine Type	Power Supply	Renewable Resources	Average Power Demand	Peak Power Demand
Spence Mine	Atacama, Chile	Copper	25+ years	Open-Pit	Grid-Connected	High Solar Irradiance, Moderate Wind Speed	53MW	75 MW
Casino Project	Yukon, Canada	Copper, Gold, Silver, Molybdenum	22 years	Open-Pit	Off-grid	Low Solar Irradiance, High Wind Speed	102MW	125 MW
Degrussa-Sandfire	North-Western Australia	Copper, Gold, Silver, Molybdenum	17 years	Underground	Off-grid	High Solar Irradiance, Moderate Wind Speed	15 MW	17 MW

SPENCE MINE - ATACAMA, CHILE Spence mine is an existing open-pit copper mine located in the Atacama Desert at 1700m above sea level near the mining town of Sierra Gorda (50km from Calama). The mining resource is based on oxide and sulphide ores with a grade of 0.89-1.24%. 50kt of ore are processed everyday using heap leaching in order to produce copper cathodes. The current mine-life is dependant on the realisation of the underground extension (Hypogene project), which might increase the mine-life by up to 37 years. The mine is located in the region that receives the highest solar radiation on earth. Moderate to high wind speeds can be measured around the mine site. The potential for biomass is relatively limited at this point due to the transportation costs between southern and northern Chile, which tend to be relatively high for biomass (i.e. low energy density). The average power demand is 53MW - currently supplied via the SING grid (Sistema Interconectado del Norte Grande). This mine is considered in this research as both grid-connected and off-grid. While there is a grid connection supplying the Spence mine, several other neighbouring mines are operating in the Atacama using off-grid diesel systems - hence the Atacama region presents a potential for both off-grid and grid-connected alternatives. The hourly power demand of the Spence mine is publicly available on the website of the dispatch centre of Northern Chile CDEC-SING.

CASINO PROJECT MINE - YUKON, CANADA The casino project is a new copper open-pit mine at 1300m above sea level that is currently in the environmental assessment phase. The mine is remotely located (300km from Whitehorse) with no access to the grid. The expected power system is CCGT and diesel according to the feasibility study (Conrad et al., 2013). The ore reserve is low-grade (0.20-0.39%) which includes copper, gold, silver, and molybdenum. The mine is expected to produce concentrate (as opposed to copper cathodes or gold bullions) with conventional milling and flotation processes. 120kt of ore is to be processed everyday. The average power demand is expected to be around 102MW while the expected mine-life is 22 years. Because there is no historical data for this mine, the dataset of a similar mine has been used instead. Specifically, the dataset of the mine Minera Esperanza in Chile was selected due to its similar characteristics (low copper grade, 97kt or ore per day, production of concentrate with milling and flotation). A linear extrapolation of the power demand was performed on the dataset of Minera Esperenza (downloaded from the CDEC-SING website) in order to adjust the dataset to the expected peak power demand of the Casino project.

DEGRUSSA-SANDFIRE MINE - NORTH-WESTERN AUSTRALIA The DeGrussa mine is a new high grade copper mine in Western Australia with a mine-life of 17 years. The ore grade is 5% for underground sulphide ore (and 1.8% for gold). The project is extremely remote with no grid connection - located 900km north of Perth and 150km north of Meekathara. The mine is producing copper and gold concentrate via a milling and flotation process. The same energy demand dataset than the Casino project was used for this mine - after a linear extrapolation to the peak power demand of the DeGrussa-Sandfire mine (15MW). This choice was made because there is no publicly available dataset of underground mines and because the selection of the dataset for power demand has little impact on results as there is very little intra-day/season variations that occur in selected mining activities (Engelhard, 2016) - as long as the selected dataset represents the energy demand of continuous processes. Because this mine is operating underground, the value of lost load is set to be substantially higher - due to the higher ore grade and the risks associated with underground mining (i.e. electricity is required to move the miners in and out the mine). A sensitivity analysis on the value of lost load is subsequently performed in section 6.4.1 on page 176 to account for these parameters.

4.3 CLIMATE DATA

Two key datasets have been used to model the energy inputs of solar and wind technologies at the geographical coordinates of selected mines. First, the Meteonorm dataset (Remund et al., 2004) is the main source of solar data for this research - further explanations on this dataset are given in section 6.1.1 on page 164 with respect to the selection of different climate scenarios. The software PVSyst was used to calculate the output of tilted and tracking PV as well as CSP plants (including direct and indirect radiation for PV and DNI for CSP). The tracking system for PV is based on a E-W axis with North

South tracking (tilt 10 degrees to 80 degrees). CSP plants are based on either a single E-W axis (tilt 90 to -90 degrees) for the North South tracking of CSP Parabolic Trough or a two-axis North South and azimuth tracking (-120 to 120 degrees) for CSP Tower.

Second, the NCEP-CFSR climate reanalysis dataset was used for wind data in HELiOS-Mining (NCEP, 2010). A neutral air flow exponent of 1/7 was applied to extrapolate the wind speed to the hub height. A number of additional modifications have been performed on this dataset in order to adjust the extrapolated outputs to the results of a mesoscale dataset (Environment-Canada, 2003) - which are further detailed in section 6.1.2 on page 165. Note that the modelling methods and data sources for both Meteonorm and NCEP-CFSR are extensively discussed in the first sections of chapter 6 on page 163 with respect to the data selection of the adequacy analysis. For reasons of simplicity, such background explanations on climate datasets were not duplicated in present chapter.

4.4 SELECTION OF TECHNOLOGICAL OPTIONS

Three mining regions have been investigated in this research. Selected mines have different peak demand, mine-life periods, and access to resources. A range of technologies have been considered in order to take into account the local resources associated with each mine. For instance, gas turbines and CCGT plants are only available in the Canadian mine as it requires significant amounts of water for cooling (Kehlhofer et al., 2009). The selection of technological alternatives in HELiOS-Mining is based on the following choices:

- Fixed PV (all mines)
- Tracking PV (all mines)
- Concentrated Solar Power (CSP) with dry-cooling - both CSP Tower and Parabolic Trough (all mines)
- Battery energy storage (all mines)
- Wind turbine (all mines) - with de-icing capabilities in icy climates
- Diesel generator (all mines)
- CCGT and gas turbines (Canadian mine only)
- Grid power (Chilean mine only)

These technologies can be combined in various ways in a hybrid renewable power system. For instance, wind and PV can be easily combined with a diesel generator (e.g.

Rehman and El-Amin, 2015); CSP and PV can be combined in order to use the PV power during the day and generate power with the CSP heat storage at times of low solar radiation or wind energy (e.g. Green et al., 2015). The choice between the various technological choices is either free or constrained in HELiOS-Mining. The first run of the optimisation is free to select, size and combine any of these technologies in order to minimise the LCOE. The following runs are constrained to generate near-optimal solutions that include different type of technological combinations. Note that near-optimal solutions refer here to power systems in which the choice of technology has been forced by the user (rather than letting the model pick the optimal power alternative). These near-optimal results are analysed in chapter 5 on page 109 to provide incremental evidence towards the optimal technological mix and generate insights on the economic viability of various types of hybrid power systems. Subsequently, all optimal and near-optimal solutions are included in a portfolio framework in the third research question in order to compare the cost risk associated with each optimal and near-optimal solutions.

4.5 TECHNICAL PARAMETERS

A number of technical parameters are necessary to accurately model the selected generation technologies. The applied technical parameters are provided in tables 4.2 on the next page and 4.3 on page 98 - although some additional details and justifications are also provided in following sub-sections. Note that POR refers to Planned Outage Rate while FOR refers to Forced Outage Rate.

4.5.1 *Availability Rate*

The availability rate (FOR + POR) was subtracted from the power capacity for wind, PV, Battery and Diesel. Because these power plants are based on several modular units, it is assumed that a forced failure on one unit can be balanced by the systems - hence not producing power shortages. For CCGT and CSP, it is assumed that 50% of the plant is to fail 350 hours per year (i.e. FOR=4%) - as the model accounts for two CSP steam turbines and the CCGT and GT plants are modelled with two independent shafts - consisting of two gas turbines and two steam generators. Because of the relative uniformity of the power load, no further temporal analysis was performed on energy security.

Table 4.2: Technical parameters for selected Wind and Solar technologies

#	Name	Efficiency	POR	FOR	Performance degradation	Selected unit size	Sources
W	Wind turbine (for climate with no significant icing events)	90% of Gross output (losses associated with array & power electronics)	0.6%	5%	<1%/yr	1.7 MW	(NREL, 2012)
W_{icy}	Wind turbine Enercon E70 2.3 MW (with additional transportation/installation costs and de-icing system)	80% of gross output (losses associated with array, power electronics, icing, and energy consumption for de-icing)	0.6%	5%	<1%/yr	2 MW	(NREL, 2012; Van Wyk, 2013)
S_{PV}^{F}	Fixed solar PV	16% of solar resources and 82% performance ratio	2%	0.01%	<1%/yr	2 MW per inverter	(Engelhard,2016; NREL, 2012)
S_{PV}^{T}	Tracking solar PV (single-axis)	16% of solar resources and 82% performance ratio	2%	0.01%	<1%/yr	2 MW per inverter	(Engelhard,2016; NREL, 2012)
S_{CSP}^{PT}	Concentrated Solar Power (Parabolic trough)	Solar resource to heat: 75% Heat to electricity: 37.5% Parasitic losses: 34% of gross efficiency Net efficiency: 18.5% Gas-to electricity: 32%	–	4%	<1%/yr	50 to 100% of CSP capacity per power block	(Engelhard,2016; Jorgenson et al., 2013; Turchi et al., 2010, Zhang et al., 2010)
S_{CSP}^{T}	Concentrated Solar Power (Tower)	Solar resource to heat: 55% Heat to electricity: 42.5% Parasitic losses: 38% of gross efficiency Net efficiency: 14.5% Gas-to electricity: 32%	5%	4%	<1%/yr	50 to 100% of CSP capacity per power block	(Engelhard,2016; Jorgenson et al., 2013; Turchi et al., 2010, Zhang et al., 2010)

4.5.2 *Wind*

Additional parameters are required to model wind power in relation to technical ratings. The chosen technical characteristics for this research are provided in table 4.4. While the same nominal efficiency is applied to both of the wind turbines presented in table 4.4, additional efficiency losses need to be accounted for wind plants that require anti-icing or de-icing systems (Parent and Ilinca, 2011). Such losses are associated with the energy requirements for either preventing or eliminating the occurrence of ice on the blades of the wind turbine. Specifically, the anti-icing approach is a preventive method that can use either an ice-phobic coating (Kimura et al., 2003) or a thermal device that heats the blade to around 0°C in order to prevent icing (Mayer et al., 2007). By contrast, the de-icing approach is applied to eliminate the ice that is already present on the blades. Such approach is usually carried out through an electric resistance that produces heat while the wind turbine is running or through a radiator blowing warm air into the rotor blade at standstill (Seifert, 2003). Battisti et al. (2006) suggests that the de-icing approaches have a significantly lower energy consumption

Table 4.3: Technical parameters for selected Storage and Fuel-based technologies

#	Name	Efficiency/Losses	POR	FOR	Performance degradation	Selected unit size	Sources
St_B	Li-Ion Energy Storage	Net efficiency: 91% (for a max 0.5 C ratio and DoD of 80%)	0.55%	2%	1.4%/yr	160 kWh per rack 3.7 MWh per container	(Engelhard,2016)
St_H	Thermal Storage i.e. Molten Salt for CSP Tower, Thermal Oil for CSP Trough	2% of heat decay overnight for CSP Tower and 7% for Parabolic trough, Heat to electricity: 42.5%	N/A	N/A		No constrains	(Engelhard, 2016, Jorgenson et al., 2013; Turchi et al., 2010)
FF_D	Diesel generator	Gross Efficiency: 34% (4-stroke medium speed)	6%	3%	<1%/yr	1/5 of peak power demand, up to 20MW per generator	(Engelhard,2016; Lazard, 2014)
FF_{GT}	Gas Turbine	28-44% (depending on output, see table 4.6)	6%	3%	>2%/yr	Half of peak power demand (two gas turbines)	(DEA, 2012; Kehlhofer et al., 2009)
FF_{CCGT}	Combined Cycle Gas Turbine	41-58% (depending on output, see table 4.6)	6%	4%	>2%/yr	Half of peak power demand (two independent single-shaft combined-cycle blocks)	(DEA, 2012; Kehlhofer et al., 2009)

than anti-icing methods. Yet, this is a relatively new area of research and a number of these technologies are not yet mature - thus there is a need for further research to characterise the actual energy efficiency of each approach (Parent and Ilinca, 2011).

Table 4.4: Wind parameters in HELIOS-Mining (TWP, 2015)

Characteristics	Enercon E82/2000	GE 1.7/100
IEC Class	IIA (medium wind speed)	IIIs (low wind speed)
Nameplate capacity	2 MW	1.7 MW
Hub height	78 m	80 m
Rotor diameter	82 m	100 m
Rated wind speed	12.5 m/s	10 m/s
Cut-in Cut-out	3 m/s 25 m/s	3 m/s 23 m/s
Total swept area	5281 m^2	7854 m^2
Features	Designed for wind speed averaging 8 m/s, gearless, de-icing, heating of the nacelle and base, reinforced steel for temp as low as – 40 °C.	Designed for wind speed averaging 6m/s.

In this research, it is assumed that wind turbines for icing climates are based on an ENERCON rotor blade de-icing system (radiator blowing air into the rotor blades). This approach is consistent with a recent mining project in Northern Canada (Van Wyk, 2013).

In such approach, a number of technical and economic characteristics need to be adjusted, including availability rate (as a function of the planned and forced outage rates), overall efficiency, and operation cost. First, the ENERCON rotor blade de-icing system requires to stop the turbine in order to eliminate the ice from the blades. This means that the model must take into consideration a higher forced outage rate (FOR) in icing climate. A more precise approach would be to derive the FOR value from detailed climatic models that take into consideration in-cloud icing (i.e. supercooled water droplets), freezing rain, wet snow, and frost (Parent and Ilinca, 2011). Such approach is computationally intensive and out of scope for this research - hence simplifying assumptions have been taken. As a result, a forced outage rate of 10% (instead of 2-5% for climates with no significant icing events) is accounted for in HELiOS-Mining. This estimate is consistent with a recent mining project in Northern Canada (Van Wyk, 2013).

Second, wind turbines in icing climate have a lower overall efficiency due to the heating demand as well as the energy losses associated with the residual frost that is not eliminated by the de-icing system - hence reducing the thermodynamic efficiency. Based on previous research, this parameter is assumed to be between 1% and 15% of the total energy consumption (Peltola et al., 2003). This parameter was estimated to be 10% in this research for the Yukon mine (Canada), as given by Maissan (2013). Further research is required to assess this parameter - hence this estimate is stated as a limitation in section 8.6 on page 222.

4.5.3 *Solar Photovoltaic (PV)*

While the power output of PV panels is relatively simple to model, a number of contextual assumptions need to be stated. First, PV plants can be relatively difficult to operate in climates prone to snowing events, sand storms, or large amount of dust - which would ultimately impact the performance ratio. The influence of these events has not been modelled and constitutes a research limitation - as stated in 8.6 on page 222. Second, the efficiency of PV panels has been reported to be ranging between 10% (i.e. amorphous silicon) and 25% (i.e. multicrystalline) (Green et al., 2011). Because a cost per kW of PV capacity is used in this research, these values only impact the space requirements of such system, which is usually not a limitation in mining settings (i.e. remote locations).

4.5.4 *CSP*

Hinkley et al. (2013) have categorised the different energy losses associated with CSP plants. As a result, the net output of a CSP Tower was found to be 14.58% of the total solar input. Specifically, the following losses have been documented in their study:

- Operational losses: include spillage and unavailability of the plant (10.7%)
- Optical losses: represent the energy losses associated with imperfect reflection of the solar resources - i.e. geometrical imperfection, shadow, low reflectivity of the mirrors, soiling, and atmospheric attenuation between the mirror and the receiver (40.1%).
- Spillage: energy losses associated with errors in positioning of the mirrors (2.84%)
- Receiver absorption losses: represent the energy losses related to the coating absorbance of the receiver (2.78%)
- Receiver thermal losses: consist of convection and radiation losses (2.04%)
- Storage & HTF losses: represent the losses associated with piping (0.34%)
- Cycle heat rejection: refers to the wasted heat from the steam turbine (24.7%)
- Parasitic losses: consist of the energy consumed to generate electricity (i.e. pumps, positioning of the heliostats) (1.9%).

In this research, CSP efficiency values were given by Engelhard (2016). CSP Tower was rated with a 23.4% gross efficiency and a 12.2% net efficiency whereas a gross efficiency of 28.1% and a net efficiency of 17.2% was applied to CSP Trough. Gross efficiency values were used in HELiOS-Mining because operational losses and spillages are separately taken into account by the model.

4.5.5 *Fuel-based generation*

4.5.5.1 *Efficiency*

The operational efficiency of gas turbines is given to be between 28% and 44% and between 41% and 58% for CCGT (DEA, 2012; Kehlhofer et al., 2009). These values vary in relation to plant sizes and the effectiveness of maintenance operations (in order to limit the heat rate degradation over-time). A range of efficiency values have been selected in HELiOS-Mining according to the plant size (see table 4.7 on page 105 for the list of efficiency values).

WATER AVAILABILITY Gas turbines and CCGT plants are only considered in the Yukon mine (Casino project) as it is the only mine that has significant water resources. On the contrary, a dry cooling approach is selected for the CSP steam turbines in Chile and Australia. Dry cooling alternatives for CCGT and gas turbines have been developed but their costs is three to four times higher than a recirculating wet cooling system. To date, all U.S. licence applications have been rejected for gas turbines/CCGT using dry cooling due to efficiency losses and higher capital and maintenance costs (Gerdes and Nichols, 2009).

4.6 ECONOMIC ESTIMATES

Various cost assumptions have been used in order to calculate the LCOE of generation options. Tables 4.5 and 4.6 on the next page provide a summary of the selected cost assumptions for this research.

Table 4.5: Costs of selected Wind and Solar technologies

#	Name	Capital cost (min-max)	Capital cost (central scenario)	Variable cost	Fixed cost (% of capital cost)	Construction time (mth)	Lifetime (yrs)	Sources
W	Wind turbine (for climates with no significant icing events)	$1200-3700/kW	$1900/kW (Victor et al., 2014) Owner costs: included	–	3%	12	25	(Engelhard, 2016; Victor et al., 2014; NREL, 2012; Lazard, 2014)
W_{icy}	Wind turbine Enercon E70 2.3 MW (with additional transportation/installation costs and de-icing system)	N/A	$2200/kW (Engelhard, 2016) (Van Wyk, 2013) Owner costs: included	–	3%	12	25	(Victor et al., 2014; NREL, 2012; Lazard, 2014; Van Wyk, 2013)
S_{PV}^F	Fixed solar PV	$1500-4300/kW	$1500/kW (Engelhard, 2016) Owner costs: 10%	–	2%	6-12	25	(Engelhard, 2016; Victor et al., 2014; Lazard, 2014)
S_{PV}^T	Tracking solar PV (Single axis East-West)	$1700-4500/kW	$1670/kW (Engelhard, 2016) Owner costs: 10%	–	2%	6-12	25	(Engelhard, 2016; Victor et al., 2014; Lazard, 2014)
S_{CSP}^{PT}	Concentrated Solar Power (Parabolic trough)	$4100-$8900/kW	Solar field & heat fluid: $250/m2 Power block: $1100/kW (Turchi et al., 2010) +20% contingency Owner costs: 10%	–	2.3%	24	25	(Engelhard, 2016; Victor et al., 2014; NREL, 2012; Turchi et al., 2010)
S_{CSP}^T	Concentrated Solar Power (Tower)	$7100-12300/kW	Solar field: $145/m2 Tower, Receiver: $230/kW$_t$ Power block: $1100/kW (Turchi et al., 2010) +20% contingency Owner costs: 10%	–	2.3%	24	25	(Engelhard, 2016; Victor et al., 2014; NREL, 2012; Turchi et al., 2010)

Other assumptions associated with these cost estimates include the following:

Table 4.6: Costs of selected Storage and Fuel-based technologies

#	Name	Capital cost (min-max)	Capital cost (central scenario)	Variable cost	Fixed cost (% of capital cost)	Construction time (mth)	Lifetime (yrs)	Sources
St_B	Li-Ion Energy Storage	Battery: $250-1750/KWh Power electronics: $100-600/kWh	Battery: $340/kWh Power converter: $150/KW Switchgear MV: $40/KW (Engelhard, 2016) Owner costs: 2%	2.5% of CAPEX (year 1-10) & 8% of CAPEX (year 11-20)	0.5%	12	10-20	(Engelhard, 2016; NREL, 2012; Nykvist et al., 2015)
St_H	CSP Thermal Energy Storage	$35-75/kWh	CSP Parabolic trough: $55/kWh-$t_t$ CSP Tower: $30/kWh-$t_t$ Owner costs: 10%	–	2.3%	24	25	(Engelhard, 2016; Victor et al., 2014; NREL, 2012; Turchi et al., 2010)
FF_D	Diesel generator	$800-1200/kW	$1050/kW (Engelhard, 2016) Owner costs: included	$4 /MWh	–	3-6	25	(Engelhard, 2016)
FF_{GT}	Gas Turbine	$780-$2100/kW	Depending on rated output (see table 4.6) Owner costs: included	$4-11 /MWh	–	24	30	(DEA, 2012)
FF_{CCGT}	Combined Cycle Gas Turbine	$1050-$1600/kW	Depending on rated output (see table 4.6) Owner costs: included	$3 /MWh	0-2%	36	30	(DEA, 2012)

- Costs are adjusted to 2015 US dollars by using the Consumer Price Index (CPI)
- Prices are given for alternative current (AC) including power electronics
- Economies of scale are solely considered for gas turbines and CCGT (justification is provided in section 4.6.5 on page 104)
- Power systems are to be built on "greenfield" sites that are reasonably levelled and clear of hazardous materials
- Mine sites have sufficient land available with respect to the space requirements of each technology (including spacing requirements of wind/solar technologies)
- Cost estimates represent the installed costs, implying that:
  - Unless noted otherwise the cost of land, construction permits, project insurance, and start-up spare parts (owner's costs) are included in capital costs
  - Unless noted otherwise, contingency costs, construction, and balance of plants are included in capital costs.
- The cost of personnel and insurance costs are either included in the variable costs or fixed costs (depending on the technology)
- The sources of the cost estimates are based on either academic literature or budgetary quotations from industry experts. All selected cost estimates have been submitted to industry experts for validation.

4.6.1 *Wind*

Two different types of wind generators are used in this research. Whereas the first type is a conventional wind turbine, the second model is designed for icing climates (e.g. Northern Canada, Alaska). The cost of the latter includes a premium for transportation, installation and supplementary technologies such as a de-icing systems that blow warm air along channels on the blades' leading edges, heaters for the nacelle and the base, reinforced steel for the base, and an adequate lubrication used in the bearings and drives (Kirby, 2014). Capital costs do not include any infrastructure costs (i.e. road) for both designs - as it is assumed that such infrastructure has already been built in order to transport the various components of the mining plant (e.g. crusher, smelter) to the mine site. The cost of wind turbines for other types of climate (i.e. non icing) is based on two recent studies on renewable energy generation (Victor et al., 2014; NREL, 2012).

The construction time is set to 12 months for both designs (NREL, 2012). This construction time is consistent with previous projects in icing climates (Van Wyk, 2013). The main challenge in icing climates being the planning phase in which there is a need to take into consideration the availability of the infrastructure at different times of the year (i.e. winter roads, boat transportation).

4.6.2 *Solar Photovoltaic (PV)*

A recent report of the IPCC has provided an array of costs for PV (utility scale) ranging between $1700 and $4300 (Victor et al., 2014). This large range can be explained by the recent decline of the cost of crystalline silicon photovoltaic systems. Specifically, it was reported that the cost of these systems fell by 57 % between 2009 and 2012 (McCrone and Finance, 2012) and further declined since then (Lazard, 2014). Based on expert opinions, the cost of fixed photovoltaic systems was set to $1500/kW in this research (Engelhard, 2016). This estimate reflects the actual installed cost that was offered to mining companies in Chile in 2015. An additional cost of $170 was added for a single-axis East-West tracking device (Engelhard, 2016).

4.6.3 *Concentrated Solar Power (CSP)*

The cost of each major CSP component (i.e. solar field, power block, heat storage) has been used in this research in order to estimate the capital cost of both parabolic trough and power tower, given by Turchi et al. (2010) and Hinkley et al. (2013). By using costs at the part level, it is possible to model any size of power capacity, storage capacity, and solar multiple - which is very useful for optimisation purposes. As a result, HELiOS-Mining is able to determine the optimal size of the power block, solar field, and thermal storage. An additional contingency cost ranging between 10% to 30% is usually added to CSP capital costs (Turchi et al., 2010; Engelhard, 2016). A central scenario of 20% was chosen for this research while a number of sensitivity analyses on capital costs have been performed in 5.3.3.4 on page 144 in order to capture the uncertainty associated with contingency costs. Costs and efficiency parameters are given for dry-cooling technologies.

4.6.4 *Li-Ion battery storage*

In this research, the battery cost per kWh is estimated to be $340/kWh[3], which is similar to the cost of the "Tesla Battery Wall" (TESLA, 2015). This cost assumption was validated by a major battery manufacturer (Engelhard, 2016)

In terms of operational costs, the variable costs of Li-Ion battery plants mostly consist of the warranty cost of the battery manufacturer - which includes spare parts and maintenance costs. This warranty cost is varying with respect to cycling and time. It is estimated to be 2.5% during the first 10 years and 8% in years 11 to 20 for one cycle per day - based on budgetary quotations from battery manufacturers (Ibid).

4.6.5 *Fuel-based generation*

The central cost scenario for diesel generation is based on the cost provided by a large genset manufacturer for a medium speed design (Engelhard, 2016). The operation costs were also provided by the same manufacturer for this generation plant. Because such power alternative is installed module by module, the potential for economies of scale is significantly lower than the natural-gas alternatives.

[3] Battery costs are further discussed in the sensitivity analysis 5.3.3.1 on page 140.

Table 4.7: Costs of CCGT and gas turbines alternatives

	Mini Gas Turbine, single cycle	**Medium Gas Turbine, single cycle**	**Large Gas Turbine, single cycle**	**CCGT, back-pressure**	**CCGT, steam extraction**
Typical size (per unit)	**0.5-5 MW**	**5-40 MW**	**40-210 MW**	**10-100 MW**	**100-400 MW**
Min Efficiency	28%	36%	35%	41%	55%
Avg efficiency	**31.5%**	**38.0%**	**39.5%**	**48.0%**	**56.5%**
Max efficiency	35%	40%	44%	55%	58%
Min capital cost per kW	$1,700		$480	$1,300	
Avg capital cost per kW	**$2,100**	**$1,450**	**$780**	**$1,600**	**$1,050**
Max capital cost per kW	$2,500		$1,080	$1,900	
Min O&M per MWh			$1		
Avg O&M per MWh	**$11**	**$8**	**$4**	**$3**	**$3**
Max O&M per MWh			$7		
Fixed cost per MW/year	-	-	-	-	$36.000

By contrast, the cost of power plants using natural-gas tends to significantly vary depending on plant size (Kehlhofer et al., 2009). Specifically, there are significant economies of scale applicable for capital costs, operating costs, and efficiency. Table 4.7 provides these different values as a function of the power rating for a single unit - based on the study of the Danish Energy Agency (DEA, 2012). These estimates are based on both measured data (1994-2006) and technical assumptions with respect to existing plants. The same cost assumptions have been applied in HELiOS-Mining[4].

Historical fuel prices and CPI indexes were obtained from the respective statistical body of each selected country: Statcan for Yukon Canada, AIP and AAA for North-Western Australia, and IEA and INE for Chile. Time-series of historical fuel prices are plotted on figure 7.2.0.1 on page 184. Biogas and biodiesel cost estimates were given by US-Dept-Energy (2015) and Foody (2014). Carbon emissions are calculated based on the estimates given by Victor et al. (2014).

[4]These cost estimates are consistent with the forecasted cost of the CCGT plant in the Casino project in Yukon, Canada - as detailed in the feasibility study published by Conrad et al. (2013).

Part III

RESULTS

5

SYSTEM COSTS

5.1 CHAPTER OVERVIEW

This chapter provides a techno-economic characterisation of cost optimal hybrid power systems for four mining contexts. The first section of this chapter on page 113 provides an overview of the approach for addressing the research question. In the second section, the results of the optimisation model are detailed along with key observations that underline the results. Section three aims on page 123 at validating these results with respect to input changes in fuel prices, mining characteristics, and capital costs. Section four on page 148 compares these input changes against two future scenarios in order to identify the most influencing factors and the key areas of uncertainty. The last section of this chapter provides a summary of the results along with a summary of input elasticities (representing the percentage of change in LCOE or renewable penetration for a 1% change in input parameter - as defined in 5.3 on page 123) as well as a summary of tipping points on page 161. A discussion on additional influencing factors and research limitations is provided in chapter 8 on page 213.

5.1.1 *Approach*

The research question addressed in this chapter is: To what extent can hybrid renewable power systems minimise electricity costs and reduce carbon emissions of the mining industry? A hybrid power system is defined here as a combination of power plants with an appropriate level of installed capacity in order to meet the power demand. Subsequently, the main outputs of this analysis are the identification of the power systems that are cost-optimal and the characterisation of the robustness of the results. A range of sensitivity analyses have been conducted on these estimates in order to validate results for different scenarios as well as identify areas of uncertainty.

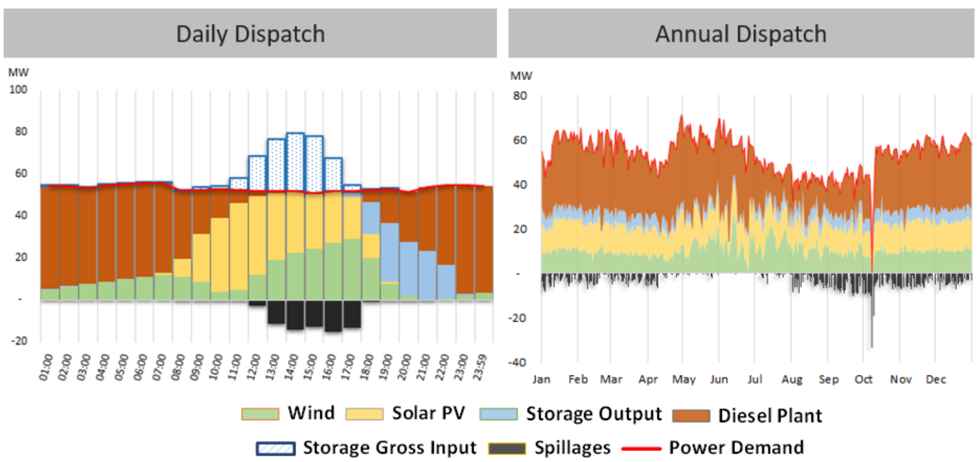
A different approach is subsequently applied in research question two and three where the trade-offs between cost-optimality, reliability, and risk factors are considered. Specifically, the cost of reliability for different climate scenarios is tackled in research question two (see chapter 6 on page 163) while the cost risks associated with future fuel prices, investment period (i.e. mine-life), and carbon taxation are analysed in the third research question (see chapter 7 on page 181).

5.1.1.1 *Visualisation of results*

The results of this study are presented with respect to several key dimensions: cost (i.e. LCOE, TLCC), carbon emissions, and renewable penetration. Yet, a variety of other dimensions are also considered in the sensitivity analyses (e.g. fuel prices, dispatch strategy). A number of comments have been directly added on the output charts in order to identify tipping points or provide useful information. A summary of the most influencing factors is also provided at the end of this section along with a table of tipping points and a summary of input elasticities (as defined in 5.4 on page 148).

The annual and daily dispatch charts of each optimal and near-optimal configurations have been placed in the appendix A along with the technical details of each power mix such as capacity factor, storage capacity, power sizes, total life-cycle costs, breakdown of the LCOE per technology, carbon emission, land use, and other outputs associated with CSP plants.

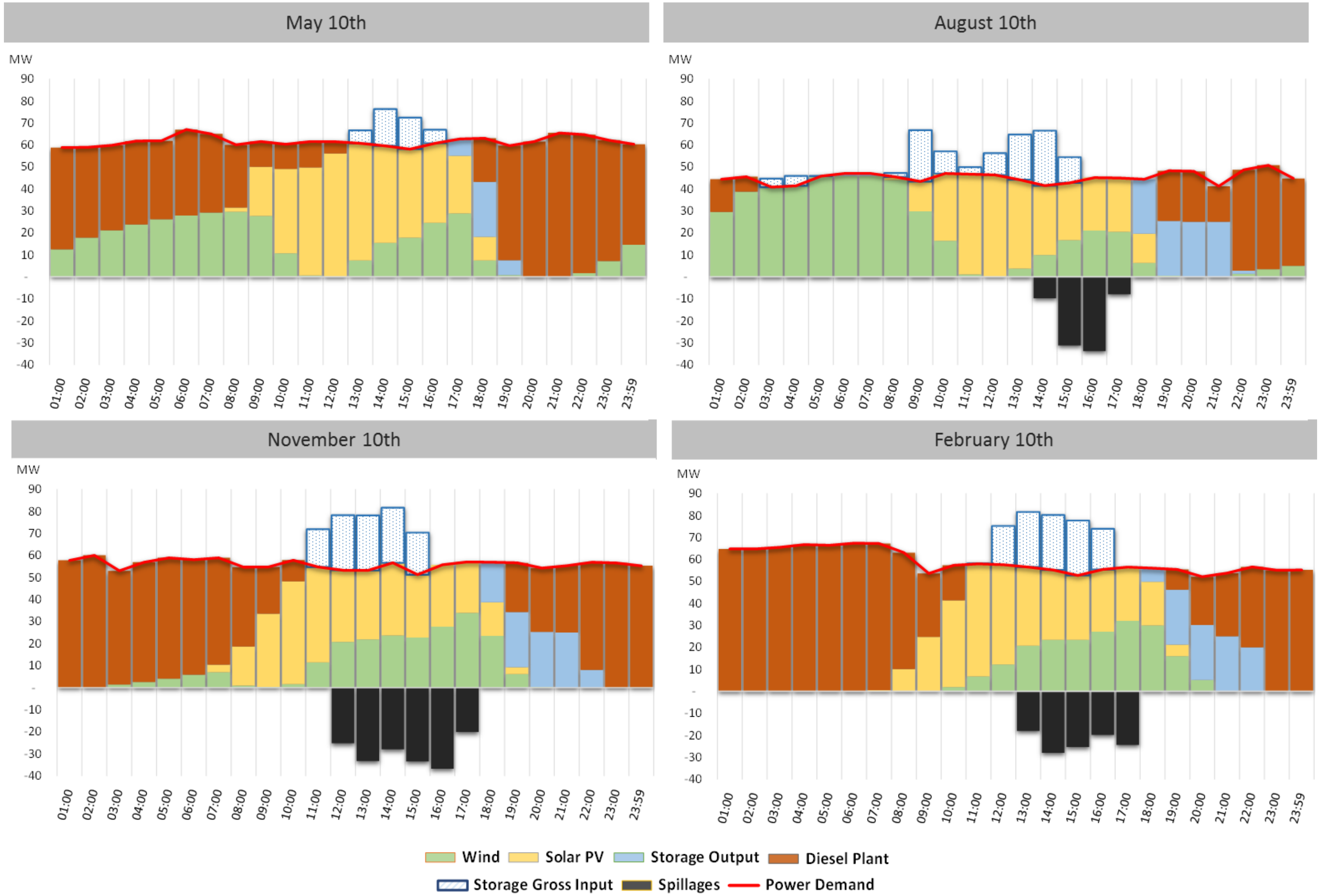
Figure 5.1: Dispatch output of a hybrid Wind/PV/Battery/Diesel power system - Average values



The chart 5.1 on the facing page illustrates the daily and annual power dispatch charts that HELiOS-Mining provides for each optimal and near-optimal scenario. A systematic visualisation of the power dispatch of each optimal and near-optimal configurations was performed to ensure that the various algorithms of the model (e.g. storage algorithm, power dispatch) are in line with the expected behaviour of each technology (and placed in appendix A).

Figure 5.2 on the next page provides further illustration of the daily dispatch in HELiOS-Mining for four selected days - as opposed to the previous dispatch chart that presents average values.

Figure 5.2: Daily dispatch of four selected days for a hybrid Wind/PV/Battery/Diesel power system (Atacama, Chile)



5.2 OPTIMISATION OF SYSTEM COSTS

5.2.1 *Optimal and near-optimal solution space*

Table 5.1 on the following page shows the optimal results of the minimisation of system costs for a number of generation mixes. These results are complemented by the amount of renewable penetration, total life-cycle costs (TLCC), and carbon savings against the baseline generation plant. The baseline is defined here as 100% diesel generation for off-grid mines and 100% grid power for the grid-connected mine, both baselines refer to common industry practices. Further technical details of the optimisation, LCOE per technology, and dispatch charts of each of these optimal and near-optimal hybrid systems are provided in appendix A on page 263.

Table 5.1: Summary of key results across four mines and three mining regions

Atacama, Chile (Off-Grid)

Technological configurations	LCOE (US$/kWh)	% Renewable	TLCC Savings	CO_2 Savings
Wind & PV & CSP Tw (Gas backup) & Diesel	0.167	80%	41%	82%
Wind & PV & CSP Tw (Gas backup)	0.185	79%	33%	82%
Wind & PV & CSP Tw & Diesel	0.185	83%	34%	83%
CSP Tw & Diesel	0.192	83%	32%	83%
CSP Pt (Gas backup) & Diesel	0.210	62%	26%	66%
Wind & PV & CSP Pt & Diesel	0.220	73%	22%	73%
PV & CSP Pt & Diesel	0.223	71%	21%	71%
Wind & PV & Battery & Diesel	0.229	49%	19%	49%
Wind & PV & Diesel	0.232	41%	19%	41%
PV & Diesel	0.236	32%	17%	32%
CSP Pt & Diesel	0.236	71%	16%	71%
PV Tracking & Diesel	0.237	32%	16%	32%
PV & Battery & Diesel	0.238	52%	16%	52%
Wind & Diesel	0.240	32%	15%	32%
Diesel only (Baseline)	0.283	0%	0%	0%
Wind & PV & Battery	0.358	100%	-15%	100%
PV & Battery	0.382	100%	-26%	100%
Wind & Battery	0.404	100%	-30%	100%

Atacama, Chile (Grid-Connected)

Technological configurations	LCOE (US$/kWh)	% Renewable	TLCC Savings	CO_2 Savings
PV & Grid	0.130	27%	7%	27%
PV Tracking & Grid	0.131	27%	6%	27%
Wind & CSP Tw & Grid	0.134	38%	4%	38%
Wind & Grid	0.134	27%	4%	27%
CSP Tw & Grid	0.136	57%	3%	57%
Grid only (Baseline)	0.140	0%	0%	0%

Optimal mix including CSP Power

Optimal mix with no CSP Power

Baseline mix

Yukon, Canada (Off-Grid)

Technological configurations	LCOE (US$/kWh)	% Renewable	TLCC Savings	CO_2 Savings
CCGT & Diesel	0.150	0%	57%	47%
Wind & CCGT & Diesel (Near-Optimal 1)	0.151	8%	57%	51%
Wind & CCGT & Diesel (Near-Optimal 2)	0.155	25%	55%	60%
GT & Diesel	0.157	0%	53%	10%
Wind & PV & Diesel	0.256	48%	21%	48%
Wind & PV & CSP Tw & Diesel	0.256	50%	21%	50%
Wind & CSP Tw & Diesel	0.259	54%	20%	54%
Wind & Diesel	0.262	38%	20%	38%
PV & CSP Tw & Diesel	0.309	18%	5%	18%
PV Tracking & Diesel	0.309	18%	5%	18%
PV & Diesel	0.309	18%	5%	18%
CSP Tw & Diesel	0.316	32%	3%	32%
Diesel only (Baseline)	0.325	0%	0%	0%

North-Western Australia (Off-Grid)

Technological configurations	LCOE (US$/kWh)	% Renewable	TLCC Savings	CO_2 Savings
CSP Tw (Gas backup) & Diesel	0.185	75%	40%	68%
PV & CSP Tw (Gas backup)	0.206	68%	32%	59%
Wind & PV & CSP Tw & Diesel	0.208	84%	33%	84%
PV & CSP Tw & Diesel	0.209	85%	32%	85%
Wind & PV Tracking & CSP Tw & Diesel	0.209	84%	32%	84%
Wind & CSP Tw & Diesel	0.209	85%	32%	85%
CSP Tw & Diesel	0.210	86%	32%	86%
Wind & PV & CSP Pt & Diesel	0.244	62%	22%	62%
Wind & PV & Battery & Diesel	0.249	55%	20%	55%
Wind & PV & Diesel	0.251	52%	20%	52%
PV & CSP Pt & Diesel	0.255	66%	18%	66%
PV & Diesel	0.260	32%	16%	32%
PV Tracking & Diesel	0.262	32%	16%	32%
PV & Battery & Diesel	0.264	52%	15%	52%
Wind & Diesel	0.265	39%	15%	39%
CSP Pt & Diesel	0.265	75%	14%	75%
Diesel only (Baseline)	0.310	0%	0%	0%
Wind & PV & Battery	0.381	100%	-16%	100%
PV & Battery	0.490	100%	-53%	100%

CSP Tw = CSP Tower

CSP Pt = CSP Parabolic Trough

A number of observations can be derived from these results, including:

- Hybrid renewable power systems provide significant economic benefits in three of the four mines analysed in this research - with life-cycle cost savings of up to 57% and carbon savings of up to 82%. Several system configurations are below the grid and diesel parity threshold - see 5.2.1.2 on page 117.
- Large range of LCOE in relation to different types of hybrid renewable power systems (also presented in the box plot 5.3 on page 117) with a minimum LCOE of US$0.13/kWh for a PV/Grid system in the Chilean grid-connected mine and a maximum of US$0.49/kWh for a 100% renewable power system composed solely of PV & Battery in North-Western Australia.
- Widely diverse levels of renewable power at mine site, from 0% for diesel generator to 100% for PV/Wind & Battery systems - as detailed in appendix A on page 263.
- Technological mixes with 100% of renewable power include large amounts of storage capacity at relatively low capacity factors and no diesel capacity - which substantially increases the cost. Power systems featuring a renewable penetration comprised between 60 and 80% of total capacity have the lowest costs in two mines and are near-optimal in three mines (see section 5.2.2.1 on page 118).
- The opportunity for including renewable energy in the mix of the grid-connected Chilean mine is relatively smaller than in off-grid mines (optimal scenario is PV & Grid with 27% of renewable energy). There is however a clear economic benefit associated with combining PV, Wind, or CSP with grid power. Further analyses on different grid constraints are given in section 5.3.1.3 on page 130.
- The Yukon mine in Canada is the only mine where the optimal scenario is entirely fossil-fuel based with CCGT & Diesel power. There are, however, two configurations in the near-optimal space of CCGT & Diesel that incorporate a significant share of wind power. These near-optimal configurations present opportunities in terms of cost risk for the research question three - i.e. trade-offs between cost and cost risk of future fuel prices (see chapter 7 on page 181).
- CSP power systems dominate the solution space in off-grid mines for Chile and Australia (including seven and eight of the first eighteen solutions respectively). The underlying factors associated with the optimality of CSP systems in off-grid mines are discussed in the section on renewable integration on page 118.
- A synergic relationship was found between the number of power plant types contained in a single hybrid power system and the system cost. Technological config-

urations with the largest number of resource types tend to have the lowest costs - as detailed in section 5.2.2.2 on page 120.

- Diesel generation remains in the mix for most technological configurations - in order to manage reliability at the lowest possible cost, as further discussed in section 6.5 on page 178. Interestingly, the diesel power capacity can be replaced by the gas-backup of the CSP plant (see configuration three in appendix A.2 on page 268) but the size of the CSP power block has to be significantly increased in order to account for the CSP low availability rate - hence drastically decreasing the capacity factor from 67% to 29% and significantly increasing LCOE levels.

These results are further analysed in following sections with respect to grid/diesel parity, renewable integration, and synergies. It should be noted that some of the hybrid configurations have been discarded by the model in cases where there was no economic benefit associated with one of the power alternative, e.g. if a hybrid power system Wind/PV/Diesel was found to be cost optimal when the size of the wind power is zero, it was assumed that there is no optimality associated with this configuration - and a PV/Diesel system should be instead considered. As a result, there are significant differences in optimal combinations of power alternatives across mines.

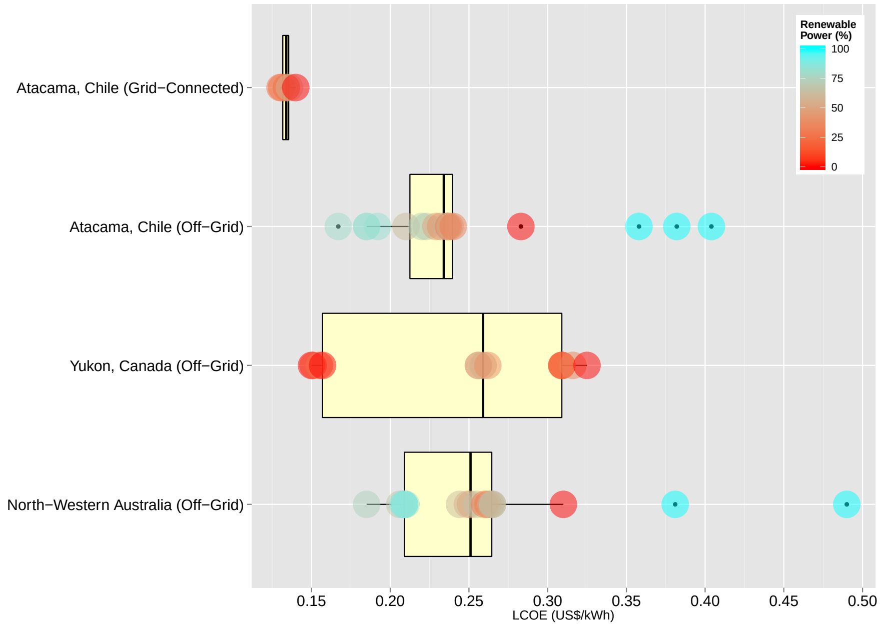
5.2.1.1 *Heterogeneity of results*

The results of the cost optimisation represent a wide range of LCOE associated with different types of hybrid power systems. As shown in figure 5.3 on the facing page, the heterogeneity of results is different depending on the location and typology of mines.

First, the Chilean grid-connected mine presents the smallest range of results due to the availability of a relatively low-cost grid power - resulting in the uncompetitiveness of most hybrid power systems. Second, the LCOE of the various mixes in the Chilean and Australia off-grid mines are mostly situated between US$0.17/kWh and US$0.26/kWh with a few outliners for 100% of renewable power.

Third, the Canadian mine has the highest heterogeneity of results with most of the LCOE situated between US$0.15/kWh and US$0.32/kWh. This large range of economic results is directly associated with the availability of renewable resources at mine site. Specifically, the Canadian mine suffers from a low amount of solar radiations and benefits from a relatively high wind speed. Together, these climate characteristics lead to a much higher cost per unit for solar-based generation and a relatively low cost of power for wind-based systems. Interestingly, the solar-based generation alternatives in Yukon

Figure 5.3: Range of cost optima and renewable penetration for different system configurations



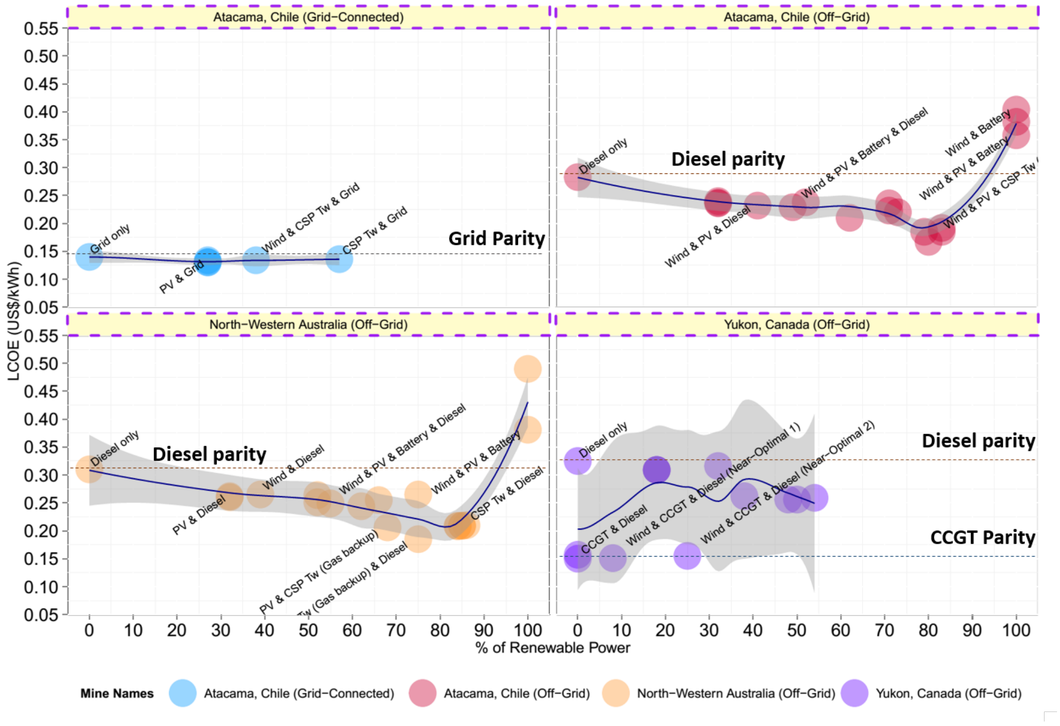
are still below the baseline of 100% diesel generation - hence emphasising the relatively high cost of diesel-based power compared to renewable alternatives.

5.2.1.2 *Parity with fuel-based power*

The previous results have identified a large number of power configurations that present a lower cost per unit than both grid power and diesel power. This means that the thresholds of grid-parity and diesel-parity have been crossed for all of the mines in-scope. However, the power alternatives featuring 100% of renewable power remain above both the diesel-parity and grid-parity - with LCOE in the range of US$0.36/kWh to US$0.49/kWh as shown in figure 5.4 on the next page. Interestingly, the CCGT parity was not reached in the Canadian mine for wind power alternatives. The interest of CCGT in mining has remained limited so far because remote mining is often confronted with problem of water availability (Soni and Wolkersdorfer, 2016) - which is not the case in the Yukon mine. Nevertheless, this result suggests that gas-power generation might present economic benefits in other mining contexts if the cost of dry-cooling gas generation were to be reduced in the future.

It should be mentioned that the grey area in figure 5.4 is a local regression (LOESS, i.e. locally weighted scatterplot smoothing) that illustrates the graphical trend of a two-dimension analysis (Jacoby, 2000); i.e. here LCOE and renewable penetration. The smoothing line is given along with the 68% confidence interval (+/- one standard deviation). The slope of this smooth line presents interesting features across all mines.

Figure 5.4: Grid/Diesel parity compared with renewable penetration for different system configurations



First, the LCOE of the Chilean and Australian off-grid mines is moving down as the level of renewable penetration increases before a sharp upward move at around 80% of renewable penetration. This sharp increase of LCOE is directly associated with the presence of diesel power in the mix. Diesel generators provide valuable power capacity at times of low availability of renewable power and consequently reduce the required size of storage capacity. Technological mixes with 100% of renewable power are constrained to include large amounts of storage capacity at relatively low capacity factors and no diesel capacity - which substantially decreases their economic competitiveness.

Second, the smooth line of the Canadian mine presents a substantially broader range of results as we move towards higher levels of renewable power. This is explained by the wider spread of system costs associated with each system configuration at higher levels of renewable penetration - hence increasing the standard deviation from the mean.

5.2.2 *Characteristics of optimal technological mixes*

5.2.2.1 *Energy Storage and Renewable Integration*

The problem of renewable integration has been widely discussed in the field of energy modelling (Weitemeyer et al., 2015; Blarke and Lund, 2008; Denholm and Margolis, 2007), e.g. solar energy can be stored during the day to be used at peak demand later in the evening. This typical scheme with peak and off-peak hours is not relevant to the mining industry. The energy demand of mining plants is characterised by a relatively stable power demand at all times of the day and night. This continuous demand of power implies that solar-based generation alternatives have to be complemented with much larger capacities of energy storage to supply power during evenings and nights. It also means that energy storage alternatives that feature low power costs and high storage costs (e.g. Li-ion battery) are likely to provide a much lower return on investment than energy storage alternatives with high power costs and low storage costs (e.g. thermal storage). The other potential solution of this problem is to complement the solar-based technologies with other renewable alternatives in order to generate power at times of low solar irradiation (e.g. wind power) and therefore reduce storage requirements (Weitemeyer et al., 2015). These technological combinations and numerous others have been thoroughly investigated in this research.

Figure 5.5: LCOE of all optimal and near-optimal technological mixes

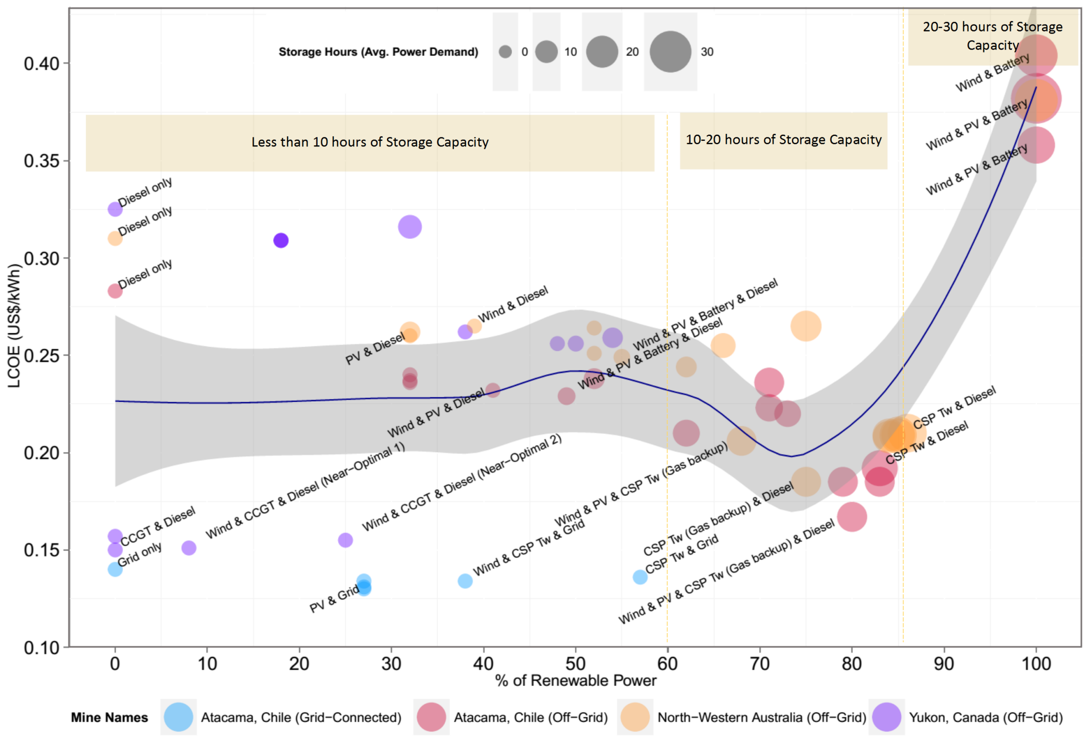


Figure 5.5 presents another perspective on the results of the optimisation by comparing the economic results of the four mining contexts with both the renewable penetration and the storage capacity (in hours of average power demand). A number of observations are given as follows:

- Most economical power systems feature high levels of renewable penetration (i.e. between 60% and 85%) combined with 10 to 20 hours of storage capacity.
- Power systems with smaller storage capacity (i.e. < 10 hours) seem to provide a lower economic return. This result was found to be directly associated with the type of storage technology, i.e. CSP thermal storage features high power costs and low storage costs resulting in large storage capacities and smaller shares of fossil-fuel power. Conversely, the wind/PV power systems with battery storage reach their optimal sizes with a smaller storage capacity and a larger penetration of fuel-based generation.
- LCOE is sharply increasing to uneconomical levels for 100% of non-dispatchable renewable power, which requires between 20 and 50 hours of battery capacity - see appendix A on page 263 for further technical details. Again, this result is directly associated with the type of storage technology. The high cost and reliability requirements of battery storage encompass that a large battery plant is required to complement non-dispatchable sources. Note that a CSP system (which is inherently dispatchable) with 100 % of renewable penetration is likely to present substantially lower costs than a PV/Wind/Battery power system. However, a combination of both CSP and diesel power was always selected by the optimisation algorithm due to the relatively low availability rate of CSP power systems.

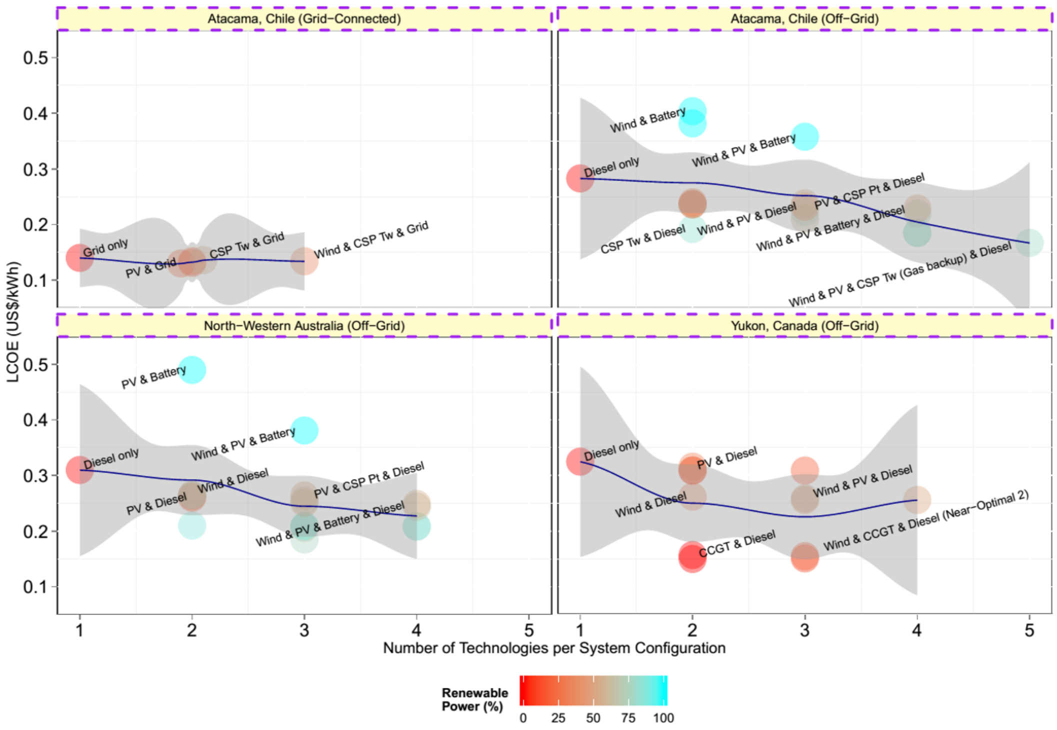
This analysis demonstrates that CSP power systems dominate the solution space in the Australian and Chilean off-grid mines. CSP alternatives are able to incorporate large amounts of low-cost storage capacities. Because of the constant power demand of mining plants, this characteristic provides a clear economic advantage to CSP plants over battery alternatives. Note that the cost of battery capacity in this analysis is based on the most recent capital valuations but further cost reductions are expected in future years (Nykvist and Nilsson, 2015). A sensitivity analysis (see 5.3.3.1 on page 140) is performed later in this chapter to further investigate this matter.

5.2.2.2 *Synergy between generation alternatives*

A number of past studies have investigated the effect of combining several intermittent technologies in order to increase renewable penetration and reduce generation costs. For instance, Nikolakakis and Fthenakis (2011) reported that the combination of wind and solar plants was found to reduce energy spillages as well as reduce storage requirements. Alternatively, Green et al. (2015) suggested that there is a synergy between PV and CSP plants and that such hybrid system is able to increase the capacity factor of the CSP plants as well as reduce generation costs. The synergy hypothesis between intermittent technologies has also been verified in the present research.

The results suggest that there is a relationship between the number of power plant types contained in a single hybrid power system, the LCOE, and the potential for renewable integration. Figure 5.6 presents this relationship for the four mining contexts. While the slope of the smooth line is showing a different strength across each mine, the LCOE of all mines tend to be decreasing when the technological diversity is increasing (also see table 5.2 on the following page).

Figure 5.6: Evolution of system costs in relation to synergies among technologies



As the number of technology increases in the mix, there is a higher potential for synergies between technologies. The following illustration of dispatch presents how synergies can be realised in a PV/CSP/CSP gas-backup/Diesel system:

1. PV provides power during the day while CSP is storing heat for later use
2. CSP thermal storage generates power at times of low irradiance at a lower price than diesel power or other alternatives
3. CSP gas-backup provides additional power capacities at times of the year when the heat capacity of the CSP thermal storage is reduced (e.g. winter time)
4. Diesel generation is "filling the gaps" and provides power when the CSP plant is unavailable (e.g. maintenance) or when the demand is higher than the power capacity of the CSP power block.

The above-mentioned example illustrates the potential for synergies among intermittent resources; numerous other examples can be found in the results of this research - for instance Wind/PV/Diesel or Wind/PV/Battery/Diesel (see appendix A on page 263). In all these configurations, the power dispatch is performed according to the merit order of each technology: the non-dispatchable alternatives are used first and the dispatchable options with the highest variable costs are the last ones to be switched on. By increasing the number of generation alternatives, the size and utilisation rate of the most expensive generation alternatives are reduced and the LCOE of the power system is optimised.

There is, however, a potential limitation associated with the uptake of multiple types of technology in a single power system. As the number of power plants increases, the size of each plant is reduced. These smaller plant sizes would negatively impact the economic return of the power system if the upper limit of the economies of scale had not yet been reached; for instance the upper limit of economies of scale was found to be 20MW for wind power (Wiser, 2014). Because of the large mine sizes in this research, it is assumed that the upper limits of the economies of scale is well below the generation size required by the mining plants (with the exception of CCGT and gas turbines for which economies of scale are considered). This should, however, be taken into consideration for smaller power systems that are subject to economies of scale.

Table 5.2: Cost reduction compared to baseline power system

	System cost as a function of baseline cost (%)				
Technologies per system configuration	**Atacama, Chile (Grid-Connected)**	**Atacama, Chile (Off-Grid)**	**North-Western Australia (Off-Grid)**	**Yukon, Canada (Off-Grid)**	**Grand Total**
1	100%	100%	100%	100%	100%
2	95%	97%	94%	77%	94%
3	96%	89%	79%	70%	89%
4		72%	73%	79%	83%
5		59%			63%

Ultimately, table 5.2 provides a numerical characterisation of the cost reduction associated with resource synergies, and further illustrates the relationship between technological diversity and cost. Specifically, it shows that technological configurations with the largest number of resource types tend to have the lowest costs - e.g. technological configurations with four or five different types of power plants have an average cost comprised between 63 and 83% of the baseline cost (i.e. diesel or grid power only).

5.3 IMPACT OF CHANGES ON OPTIMAL BASE CASES

The economic and technical assumptions of an energy model are subject to change and inaccuracy. The following sensitivity analyses aim to mitigate this issue by testing the stability and sensitivity of the results against different input parameters. The significance of conducting sensitivity analyses has been widely recognised in the economic and modelling literature. For instance, Fiacco (1984) states that "[a] sensitivity and stability analysis should be an integral part of any solution methodology. The status of a solution cannot be understood without such information. This has been well recognised since the inception of scientific inquiry and has been explicitly addressed from the beginning of mathematics".

The purpose of sensitivity analyses given by Pannell (1997) is to provide the following information: "1. how robust the solution is in the face of different parameter values; 2. under what circumstances the optimal solution would change; 3. how the optimal solution changes in different circumstances; 4. how much worse off the decision makers would be if they ignored the changed circumstances and stayed with the original optimal strategy or other strategy." In this context, the following sections aim at understanding these criteria with respect to the optimal solutions of this chapter.

The results of this study suggest that CSP systems are part of the optimal power mix in two out of four mining contexts (and 3% above the optimal LCOE in a third mine). They are, however, the most capital intensive options with the longest payback periods. While the consideration of the risk associated with capital intensity is not the subject of this chapter (see chapter 7 on page 181 for a detailed risk analysis), a distinction between CSP and non-CSP systems was made in order to not limit the results of the sensitivity analyses to CSP systems. Consequently, two base cases are considered for each mining context: CSP base case and no-CSP base case. The CSP base case refers to the optimal power mix that includes CSP power (in conjunction with other technologies) whereas the no-CSP base case refers to the optimal power mix that can include all technologies but CSP. The technical and economic details of each base case are presented in table 5.3 on page 125. Note that the Canadian mine has only a no-CSP base case due to the relatively low economic returns of CSP systems in low solar radiation contexts.

Tipping points for fuel switching as well as various input elasticities are calculated in order to understand the impact of each parameter. The elasticity of LCOE is defined as the percentage of change in LCOE for 1% change in input parameter such as $e_{LCOE} = \frac{\%\triangle LCOE}{\%\triangle Input}$. The elasticity of demand represents the percentage of change in renewable penetration for a 1% change in input parameter such as $e_{ren} = \frac{\%\triangle Ren}{\%\triangle Input}$. A summary of all elasticities is provided at the end of this chapter (see table 5.4 on page 158).

A new optimisation run is performed for each change of input parameter in the following sections. The justification for each variable change (and its upper and lower limits) is given in the respective section of each sensitivity analyses (when appropriate). Combinations of variable changes are provided for fuel prices in section 5.3.1.4 on page 131 and capital costs in section 5.3.3.5 on page 147.

Table 5.3: Optimal mixes for CSP and no-CSP base cases

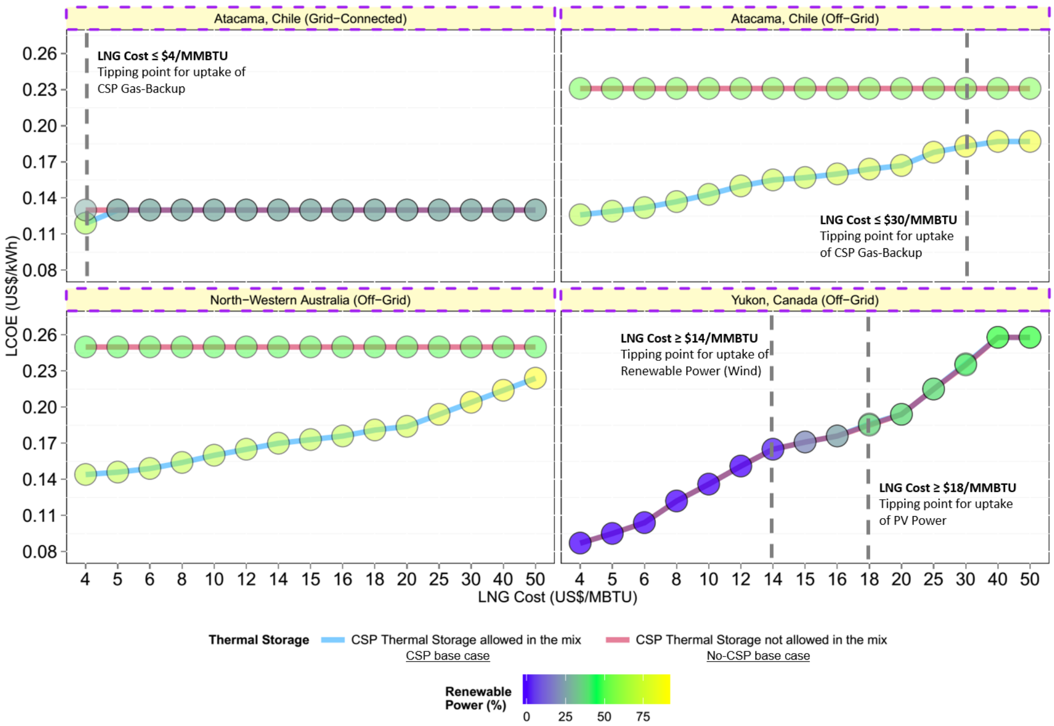
Mine	Base Case	Technology		Size	Capacity Factor	% of Total Energy Supply	Total Output (yearly)	Total Curtailment (yearly)	Net LCOE (minus spillages)	Gross LCOE (includes spillages)	Capital Cost	TLCC	Life Cycle Direct Emissions ($KtCO_2eq$)
Atacama, Chile (Grid-Connected)	No-CSP Base Case	**PV & Grid**	PV Tilted	66 MW	22%	27%	128 GWh	5.8 GWh	$0.103/kWh	$0.099/kWh	$109 M	$122 M	
			Grid	Existing grid connection		73%	340 GWh		$0.140/kWh			$439 M	7,310
			Power System			**100%**	**468 GWh**	**5.8 GWh**	**$0.130/kWh**		**$109 M**	**$561 M**	**7,310**
			Reliability	*100%*	*Renewable Energy*	*27%*							
			Hours of Storage (avg. dmd)	*0.0*	*Self-generation*	*27%*							
	CSP Base Case	**Wind & CSP Tower & Grid**	Wind	52 MW	24%	24%	111 GWh	1.4 GWh	$0.117/kWh	$0.115/kWh	$99 M	$120 M	
			CSP Tower	27 MW	67%	14%	65 GWh	3.2 GWh	$0.137/kWh		$71 M	$82 M	0
			CSP Power Block	11 MW									
			Thermal Storage	136 MWh									
			Grid	Existing grid connection		62%	292 GWh		$0.140/kWh			$377 M	6,282
			Power System			**100%**	**468 GWh**	**4.6 GWh**	**$0.134/kWh**		**$169 M**	**$579 M**	**6,282**
			Reliability	*100%*	*Renewable Energy*	*38%*	*CSP Net Eff.*	*14.2%*					
			Hours of Storage (avg. dmd)	*2.5*	*Self-generation*	*38%*	*CSP Backup*	*0.0%*					
Atacama, Chile (Off-Grid)	CSP Base Case	**Wind & PV & CSP Tower (Gas backup) & Diesel**	Wind	11 MW	25%	5%	24 GWh	0.2 GWh	$0.116/kWh	$0.115/kWh	$21 M	$25 M	
			PV Tilted	40 MW	23%	17%	81 GWh	0.6 GWh	$0.100/kWh	$0.099/kWh	$66 M	$74 M	
			CSP Tower	121 MW	67%	75%	352 GWh	36.1 GWh	$0.169/kWh		$343 M	$550 M	1398
			CSP Power Block	60 MW									
			Thermal Storage	738 MWh									
			Diesel (rated)	45 MW	3%	2%	11 GWh		$0.696/kWh		$47 M	$71 M	209
			Diesel (de-rated)	38 MW									
			Power System			**100%**	**468 GWh**	**36.9 GWh**	**$0.167/kWh**		**$478 M**	**$721 M**	**1,607**
			Reliability (EIR)	*100.00%*	*Renewable Energy*	*80%*	*CSP Net Eff.*	*13.1%*					
			Hours of Storage (avg. dmd)	*13.8*	*Self-generation*	*100%*	*CSP Backup*	*17.9%*					
	No-CSP Base Case	**Wind & PV & Battery & Diesel**	Wind	54 MW	22%	19%	105 GWh	12.4 GWh	$0.129/kWh	$0.115/kWh	$103 M	$125 M	
			PV Tilted	69 MW	21%	23%	125 GWh	14.9 GWh	$0.111/kWh	$0.099/kWh	$114 M	$128 M	
			Battery Power	25 MW	14%	7%	30 GWh		$0.365/kWh		$52 M	$66 M	
			Battery Storage	136 MWh									
			Diesel (rated)	85 MW	38%	51%	241 GWh		$0.300/kWh		$90 M	$667 M	4,518
			Diesel (de-rated)	73 MW									
			Power System			**100%**	**501 GWh**	**27.3 GWh**	**$0.230/kWh**		**$362 M**	**$988 M**	**3,072**
			Reliability (EIR)	*100%*	*Renewable Energy*	*52%*							
			Hours of Storage (avg. dmd)	*2.5*	*Self-generation*	*100%*							
Yukon, Canada (Off-Grid)	No-CSP Base Case	**CCGT & Diesel**	Diesel (rated)	77 MW	12%	8%	72 GWh		$0.427/kWh		$81 M	$271 M	1,181
			Diesel (de-rated)	70 MW									
			CCGT (rated)	123 MW	80%	92%	824 GWh		$0.123/kWh		$197 M	$828 M	6,705
			CCGT (de-rated)	117 MW									
			Power System			**100%**	**895 GWh**	**0.0 GWh**	**$0.150/kWh**		**$278 M**	**$1,099 M**	**7,886**
			Reliability	*100%*	*Renewable Penetration*	*0%*							
			Hours of Storage (avg. dmd)	*0.0*	*Self-generation*	*100%*							
North-Western Australia (off-grid)	CSP Base Case	**CSP Tower (Gas backup) & Diesel**	CSP Tower	43 MW	86%	98%	120 GWh	8.4 GWh	$0.173/kWh		$108 M	$166 M	317
			CSP Power Block	16 MW									
			Thermal Storage	191 MWh									
			Diesel (rated)	9 MW	2%	2%	2 GWh		$0.894/kWh		$9 M	$13 M	23
			Diesel (de-rated)	8 MW									
			Power System			**100%**	**122 GWh**	**8.4 GWh**	**$0.184/kWh**		**$117 M**	**$179 M**	**340**
			Reliability	*100%*	*Renewable Energy*	*76%*	*CSP Net Eff.*	*13.7%*					
			Hours of Storage (avg. dmd)	*13.7*	*Self-generation*	*100%*	*CSP Backup*	*22.9%*					
	No-CSP Base Case	**Wind & PV & Battery & Diesel**	Wind	21 MW	18%	26%	34 GWh	7.0 GWh	$0.174/kWh	$0.144/kWh	$40 M	$47 M	
			PV Tilted	21 MW	19%	26%	34 GWh	7.0 GWh	$0.142/kWh	$0.117/kWh	$35 M	$38 M	
			Battery Power	4 MW	13%	4%	4 GWh		$0.446/kWh		$8 M	$10 M	
			Battery Storage	21 MWh									
			Diesel (rated)	18 MW	37%	45%	55 GWh		$0.332/kWh		$19 M	$145 M	698
			Diesel (de-rated)	17 MW									
			Power System			**100%**	**127 GWh**	**14.0 GWh**	**$0.249/kWh**		**$101 M**	**$240 M**	**698**
			Reliability	*100%*	*Renewable Energy*	*57%*							
			Hours of Storage (avg. dmd)	*1.5*	*Self-generation*	*100%*							

5.3.1 *Impact of varying fuel prices*

5.3.1.1 *Natural Gas*

The sensitivity analysis on the price of natural gas measures the change in LCOE and technological mix for different price scenarios - along with tipping points at which LNG fuel becomes economical or uneconomical to use in the power supply. Figure 5.7 presents the results in relation to four mining contexts. The range of variable changes is extremely wide in this analysis due to the different transportation options associated with LNG. The lower limits ($4/MMBTU) relates to the minimum LNG price of the last fifteen years (using a gas pipeline) while the higher limits relates to high cost trucked-LNG. The cost of trucking LNG is context-dependant and has been estimated at $12/MMBTU for transportation costs only in Northern Chile (Engelhard, 2016). Historical LNG fuel prices are given in appendix C.3 on page 303 while historical LNG power costs are given in section 7.2 on page 185.

Figure 5.7: LCOE and renewable penetration as a function of LNG cost



YUKON, CANADA: The base case for the Yukon mine is CCGT & Diesel power, no renewable capacity, and a LNG cost of $12/MMBTU. This cost includes the price of the natural gas and the distribution to the mine. A sensitivity analysis on LNG price is particularly relevant for the Canadian mine because of the current uncertainty associated with the construction of new fuelling options: gas-pipeline, combination of gas-pipeline and trucked-LNG, trucked-LNG only, or electrification of the mine (EMR-Yukon, 2010). As a result, the price of the natural gas is set to be different depending on which option is selected. The optimisation of these fuelling routes was not in the scope of this study but it could be considered in future work. Yet, various insights can be derived from varying the LNG price in the optimisation model, presented as follow:

1. The price elasticity of LCOE is 0.51 (i.e. LCOE increases by 0.51% for 1% increase of LNG price) whereas the price elasticity of renewable penetration is 2.33 (i.e. renewable penetration increases by 2.33% for 1% increase of LNG price).
2. There is a positive uptake of renewable power with 7MW of wind capacity at $14/MMBTU - reaching 77MW of wind capacity at $15/MMBTU. The wind capacity continues to increase up to 146 MW of capacity at $18/MMBTU and remains stable at higher price levels.
3. There is a positive uptake of PV power starting at $18/MMBTU with 5MW of capacity - and up to 118MW of PV capacity at $40/MMBTU.

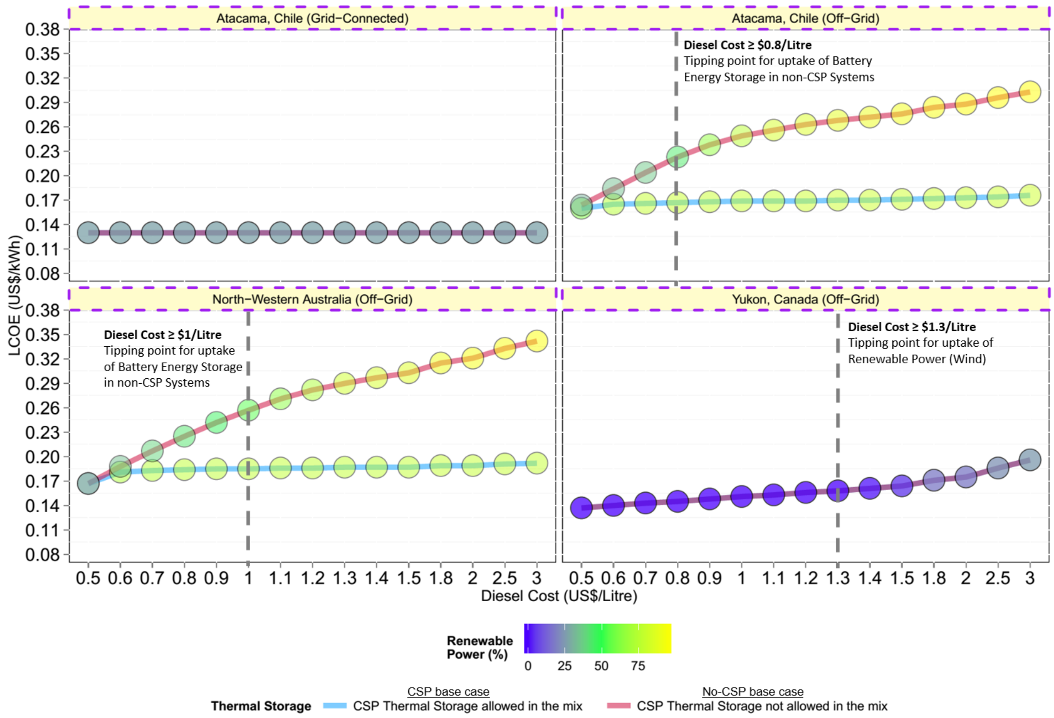
ATACAMA, CHILE / NORTH-WESTERN AUSTRALIA: The central LNG price assumption for those mines is $20/MMBTU (i.e. trucked-LNG only, no access to gas pipelines). The price change of this analysis is only impacting CSP-systems using gas-backup; CCGT and gas turbines were only considered for mines with significant water resources (due to cooling requirements).

1. The CSP base case is inelastic to change in LNG prices with price elasticities of LCOE at approximately 0.23 in both mines; and a price elasticity of renewable penetration at 0.18 in the Chilean mine and 0.25 in Australian mine.
2. The share of the CSP gas-backup is incrementally decreasing for both off-grid mines as the LNG price is increasing. Yet, a low penetration of CSP gas-backup remains competitive at $30/MMBTU in the Chilean mine and $50/MMBTU in the Australian mine.
3. CSP gas-backup is not a competitive option in the Chilean grid-connected mine except for LNG prices equal or inferior to $4/MMBTU - which is highly unlikely without a gas pipeline (as transportation costs of trucked-LNG are estimated to be $12/MMBTU).

5.3.1.2 *Diesel*

The sensitivity analysis on the price of diesel fuel measures the change in LCOE and technological mix for different price scenarios. Figure 5.8 presents the results in relation to the four mining contexts of this research. The range of diesel prices is determined based on two standard deviations above or below the mean of the forecasted diesel price - as shown in figure C.1 on page 301.

Figure 5.8: LCOE and renewable penetration as a function of diesel cost



ATACAMA, CHILE / NORTH-WESTERN AUSTRALIA (OFF-GRID): The CSP base case features a price elasticity of LCOE at 0.04, and a price elasticity of renewable penetration at 0.07 and 0.09 in the Chilean and Australian mine respectively. As a result, the diesel capacity is incrementally replaced by a larger share of gas-backup as the diesel price is increasing.

The no-CSP base case features substantially higher elasticities, with a price elasticity of LCOE at 0.41 and 0.49, and a price elasticity of renewable penetration at 0.89 and 0.86 in the Chilean and Australian mine respectively. Consequently, higher diesel price levels lead to significant technological changes and a gradual increase of storage and renewable capacities. Battery storage is the most significant change with an uptake of up to 42% of the power supply at $2/litre.

YUKON, CANADA (OFF-GRID): The price elasticity of LCOE is 0.21 and the price elasticity of renewable penetration is 1.86. There little or no changes in the share of natural gas generation as the diesel price is increasing or decreasing. The diesel capacity remains necessary at all price levels in order to provide backup generation to the CCGT plant. Wind power is entering in the optimal mix at $1.3/litre and wind capacity is gradually increasing as the fuel price continues to level up - whereas the capacity factor of the diesel plant is decreasing.

5.3.1.3 *Grid*

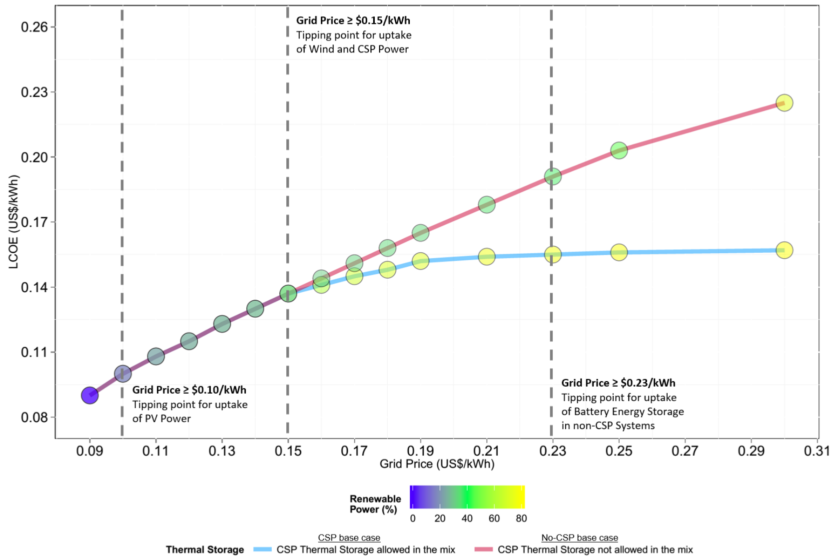
The sensitivity analysis on grid price has only been conducted for the Chilean mine. The Chilean mining industry is context-specific as it is located in the nearby areas of the SING power network - with 90% of the SING power capacity dedicated to the mining industry (Parrado et al., 2016). Other mines considered in this research are relatively distant from network connections and therefore much more prone to implement off-grid systems. Yet, the potential for grid extension remains a relevant issue; although arduous to accurately cost due to the difficult topographies of mining regions. The LCOE estimates given in this analysis are, however, a good proxy for assessing the maximum cost of future grid-connections. A discussion on grid-connection alternatives is provided in chapter 8 on page 213.

GRID PRICE: This analysis presents the evolution of the LCOE and renewable penetration for different levels of grid prices. These prices include all the costs of supplying grid power directly to the mine site (e.g. generation, distribution). The central assumption for grid price in Northern Chile is $0.14/kWh. Note that the exact grid price is confidential and might vary for each mining customer of the Atacama region. The range of grid prices was estimated to be between $0.13/kWh and 0.18/kWh based on discussions with power managers of various Atacama mines (Engelhard, 2016). Interestingly, Grageda et al. (2016) have reported that grid prices have been recently increasing due to lower rainfall, drought, natural gas shortages, and earthquakes.

The results presented in figure 5.9 suggest that there is a significant relationship between grid price and renewable penetration. Specifically, the price elasticities of LCOE are 0.52 and 0.78 while the price elasticities of renewable penetration are 1.85 and 0.61 in the CSP and no-CSP base cases respectively (for grid prices between $0.12 and 0.21/kWh). There is a positive uptake of PV power for all grid prices equal or superior to 0.10/kWh whereas CSP power is only economically viable at $0.15/kWh. In the CSP base case, the

LCOE of the power system is levelling off for all grid prices above 0.19/kWh as the grid power is almost completely replaced by renewable alternatives (i.e. CSP, Wind, Solar PV). Conversely, the LCOE increases linearly with the grid price in the no-CSP base case. This provides further evidence of the economic competitiveness of CSP thermal storage over battery plants for the constant load requirements of continuous mining processes.

Figure 5.9: LCOE and renewable penetration as a function of the grid power price (Atacama, Chile)



CAPACITY FIRMING: The implementation of non-dispatchable generation in a grid-connected mine means that the grid operator is required to intermittently balance the power demand of the mine. Such requirements lead to higher generation costs for utilities and clients, i.e. part loading and lower generation efficiency. This is particularly relevant in the Atacama region due to the relatively constant load curve of the SING power network. Different strategies can be adopted to mitigate this problem.

First, the utility company can refuse to supply intermittent power to the mine. In this case, the mine would be able to purchase a constant power output from the grid and complement it with an off-grid system including renewable generation, storage, and backup power. The cost of this option would be relatively similar to the off-grid power systems presented in earlier sections. Second, the utility company could increase power costs to mitigate the inefficiencies associated with plant cycling (see figure 5.9 for the sensitivity analysis on grid price). Finally, the implementation of a capacity firming strategy would limit the impact of intermittent resources on generation plants. In this strategy, the mine is required to supply a minimum guaranteed output to power its activities while the grid is firming up the remaining capacity, as illustrated in figure 5.11 on the following page.

Figure 5.10: Evolution of the LCOE in relation to a capacity firming strategy in a grid-connected mine (Atacama, Chile)

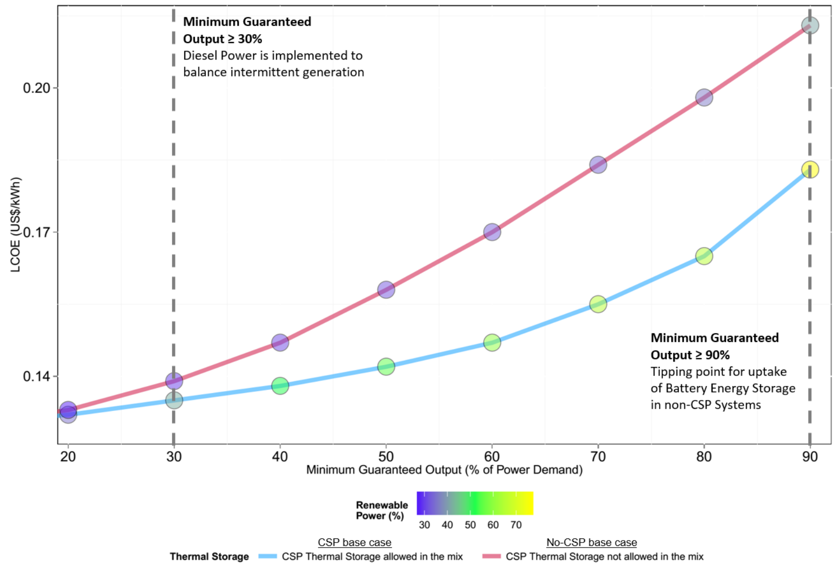


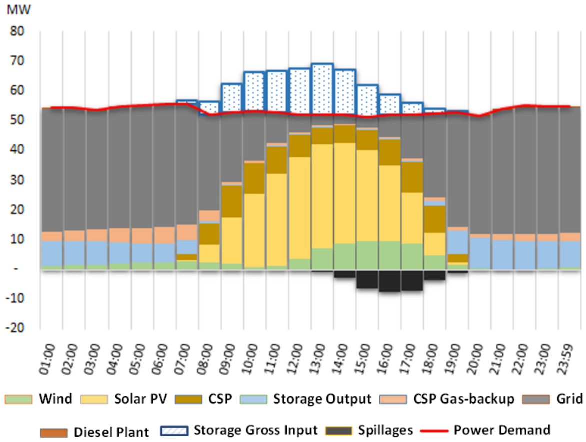
Figure 5.10 presents the impact of different levels of capacity firming on the LCOE. The elasticities of the LCOE are 0.05 and 0.01 while the elasticities of renewable penetration are 0.33 and 0.07 in the CSP and no-CSP base cases respectively - expressing the change in LCOE and renewable penetration for 1% additional unit of minimum guaranteed output for a range of input change between 0% and 50%. This result stresses that the CSP base case is more sensitive in terms of renewable penetration and less sensitive in terms of cost per unit i.e. LCOE.

Further, it can be observed that the slope of the LCOE curve is relatively mild in the CSP base case for minimum guaranteed outputs between 20% and 70% - levels at which CSP plants reach optimal size and capacity factor. Higher levels of minimum guaranteed outputs are associated with larger shares of diesel capacity, lower capacity factors, and higher LCOE levels. On the contrary, the LCOE of the no-CSP base case is linearly increasing with larger uptake of diesel power and non-dispatchable renewable capacity in the mix - which further stresses the gap between CSP systems and non-dispatchable alternatives.

5.3.1.4 *Year-on-Year Fuel Price Increase (real inflation)*

This sensitivity analysis measures the change in LCOE and technological mix for a similar increase of year-on-year fuel prices over the investment period. While previous sensitivity analyses have considered each fuel independently, it is assumed here that there is

Figure 5.11: Average daily dispatch with 20% minimum guaranteed power output



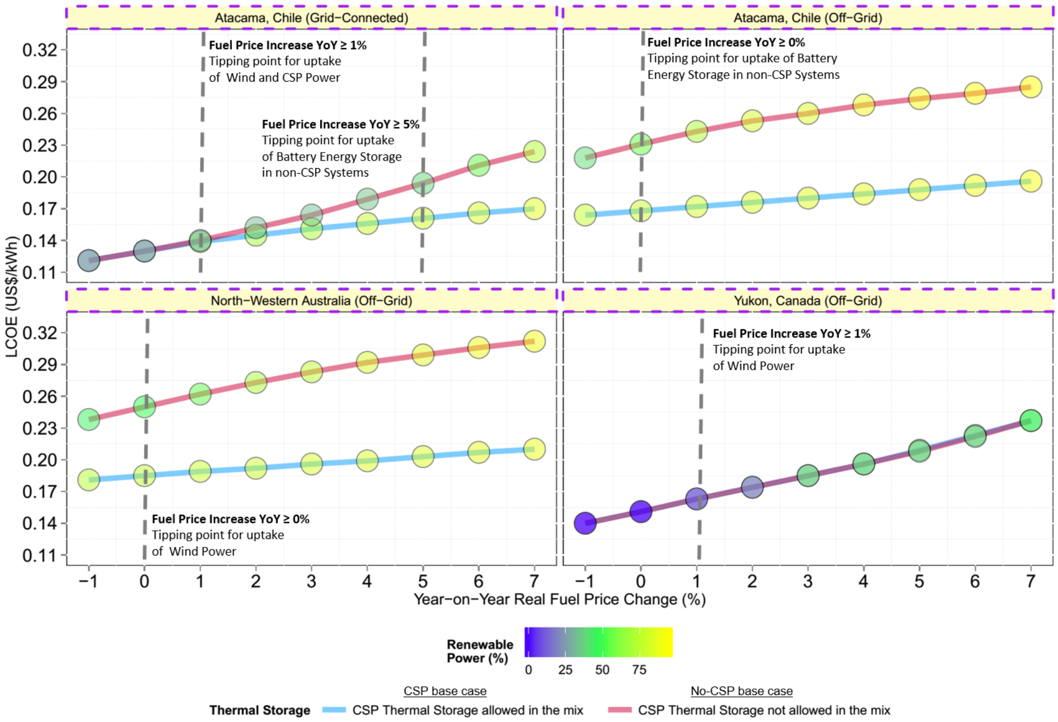
a perfect correlation between the prices of natural gas, diesel, and grid power. It should be mentioned that past studies have provided lower correlation scores for fuel price changes. For instance, Shafiee and Topal (2010) have found that the nominal prices of oil and natural gas had a correlation coefficient of 0.95 between 1950 and 2008. In spite of this caveat, interesting insights can still be drawn.

This analysis is relevant in light of the high uncertainty associated with future fuel prices. Whereas the central scenario of the optimisation accounts for a neutral increase of real fuel prices, historical data suggest than fuel prices tend to increase faster than other goods. Specifically, the rate of change of historical fuel prices corrected for inflation was found to be averaging between 2.5% and 5.6% year-on-year from 1999 to 2015 - depending on the selected country (see 7.2 on page 185).

Based on the results of this analysis presented in 5.12, a number of observations can be made:

1. Significant impact on the LCOE with up to 31% of relative LCOE increase and a 45% absolute increase of renewable penetration for a 3% year-on-year increase of fuel prices.
2. The slope of the LCOE curve is milder for the CSP base case due to the smaller share of fossil-fuel generation.
3. Wind power is an economically viable option in the Yukon mine for a 1% increase of year-on-year real fuel prices - which is a plausible outlook based on historical fuel prices.
4. Price elasticities are the most sensitive for the Chilean grid-connected and the Yukon mines due lower amounts of renewable in the mix (see table 5.4 on page 158).

Figure 5.12: Sensitivity analysis on the year-on-year inflation of all fuel prices



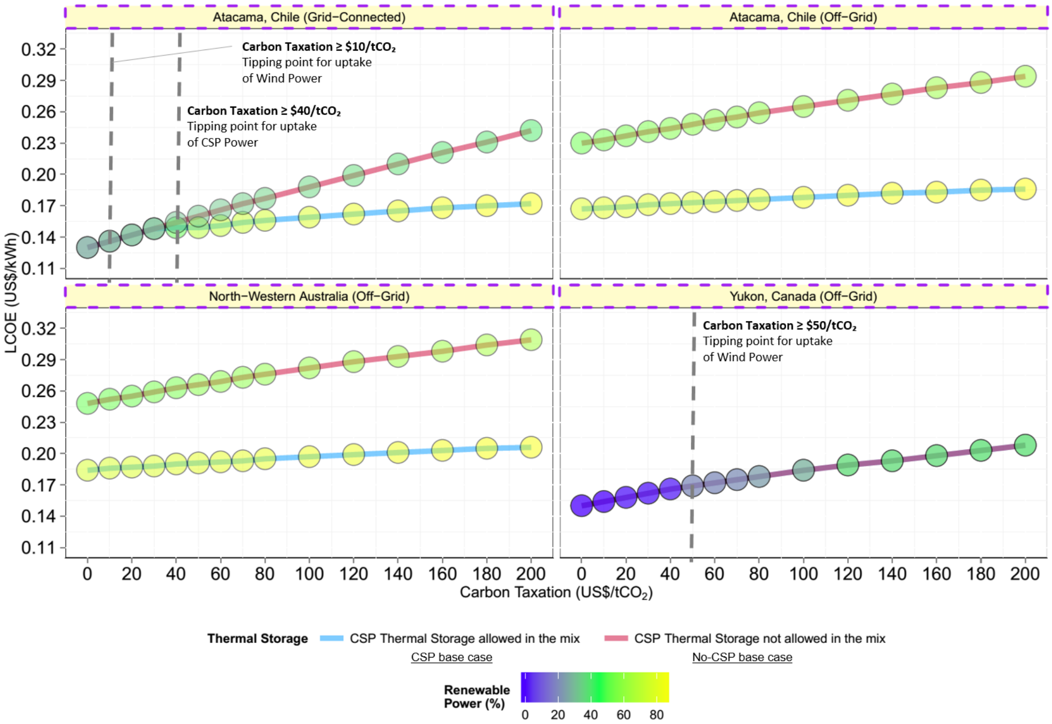
These results further point out that a higher share of renewable penetration can hedge off the risk associated with the uncertainty of future fuel prices. This is a major competitive advantage of renewable technologies over fuel-based alternatives. A number of past studies have presented similar findings (Bolinger, 2009; Awerbuch, 2000; Jansen et al., 2006) but this research is the first that involves the mining industry. Further characterisation of fuel price uncertainty is given in chapter 7 on page 181 as part of the third research question.

5.3.1.5 *Carbon Taxation*

The sensitivity analysis on carbon taxation measures the change in LCOE, fuel mix / capacity factor, and technological mix for different scenarios. The results are presented in figure 5.13. Note that the four mining regions of this analysis have currently no taxation on carbon emissions (discussed in section 8.3 on page 216).

Similarly to the analysis on fuel price, the results suggest that a higher proportion of renewable power is hedging off the added-cost of carbon taxation. The slope of the LCOE curve is milder for the CSP base case due to higher renewable penetration levels. Interestingly, a small carbon taxation of \$10/tCO_2 leads to higher levels of renewable penetration in the grid-connected mine and there is a positive uptake of wind power at \$50/tCO_2 in the Yukon mine. Higher levels of carbon taxation are associated with in-

Figure 5.13: LCOE and renewable penetration as a function of the level of carbon taxation

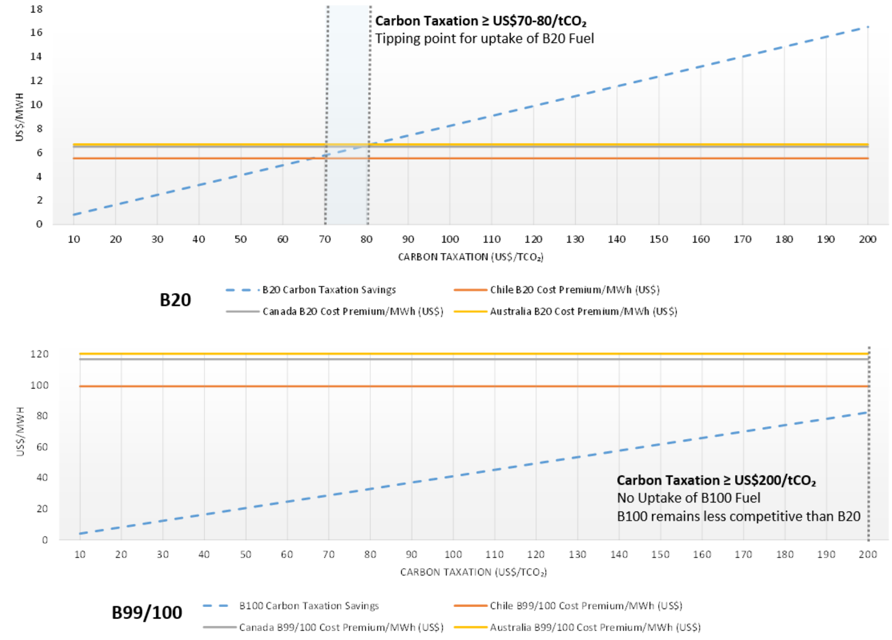


creasing penetration of renewable energy in all mining contexts with up to 52% absolute increase of renewable penetration at 50$/t$CO_2$ (i.e. uptake of a large CSP system in the grid-connected Chilean mine).

Interestingly, it can also be observed than the highest levels of carbon taxation are not associated with 100% of renewable capacity. At $200/t$CO_2$, the renewable penetration reaches between 87% and 89% of the power supply in the Chilean and Australian mines respectively (CSP base case). Consequently, fuel-based power plants still provide an economic contribution to the power system for backup generation as well as optimisation of capacity factors and sizes of renewable plants. The economic value of fuel-based plants with low capacity factors is discussed in 6.5 on page 180 whereas the risk associated with future carbon prices is analysed in 7.3.3 on page 195.

BIOFUELS: B-20 biodiesel (i.e. 20% blend) is included in the mix for carbon prices situated between $70 and $80/t$CO_2$ whereas the B99/100 (i.e. 99/100% blend) biodiesel is not competitive at current prices for any level of carbon taxation. Figure 5.14 presents the tipping points of each biodiesel in relation to different levels of carbon taxation. Note that a biogas alternative was also included in the model but was systematically discarded by the optimisation algorithm, due to the current high cost premium associ-

Figure 5.14: Tipping points for uptake of biodiesel: B20 and B99/100



ated with this fuel. A discussion on alternative biofuels is also provided in chapter 8 on page 213.

5.3.2 *Impact of varying mine characteristics*

Three different sensitivity analyses associated with discount rate, demand-shifting, and investment periods are presented as follow.

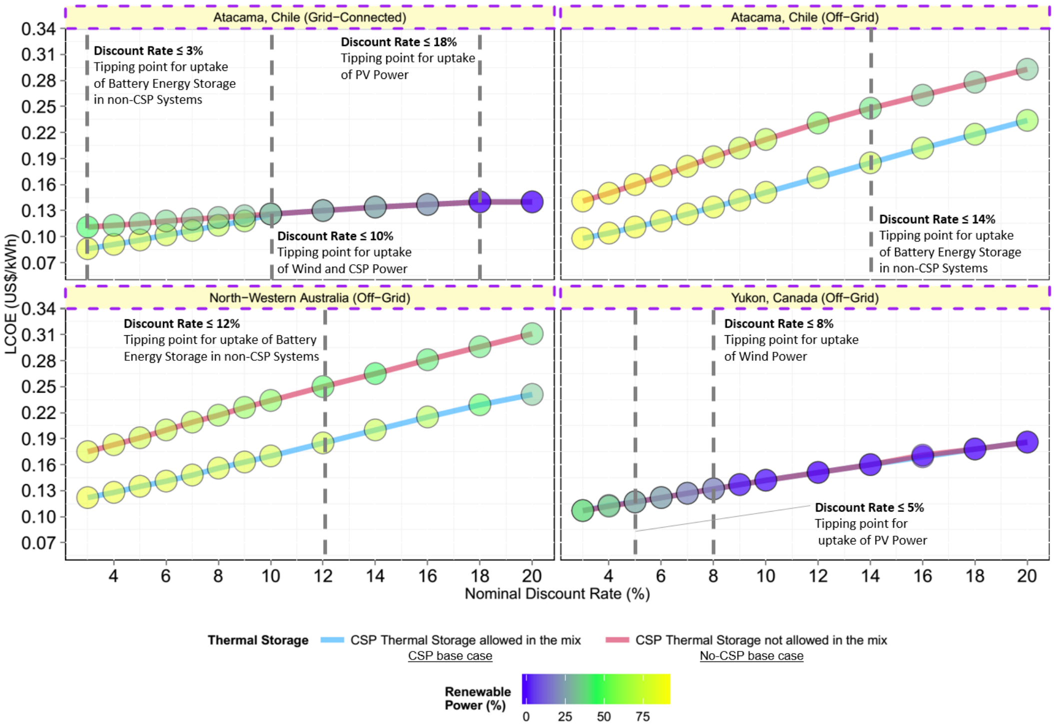
5.3.2.1 *Discount Rate*

The sensitivity analysis on discount rates measures the change in LCOE, and technological mix for different discount rates. Results are presented in figure 5.15. Note that a nominal discount rate of 12% is applied in the base cases for the four mining contexts (as given in section 3.6.6 on page 65).

A number of useful insights can be derived from this analysis:

1. High discount rates tend to be associated with a lower penetration of renewable resources due to the relationship between the discounting of future cash flows and the level of capital intensity.
2. The slope of the LCOE curve is relatively steep for all off-grid mines with a doubling of the LCOE when varying the nominal discount rate from 3% to 20%.

Figure 5.15: LCOE and Renewable penetration as a function of the nominal discount rate



3. CSP power systems remains economically viable for high discount rates ranging between 10% and 14% (with the exception of the Yukon mine where CSP is never a viable option).
4. Positive uptake of both PV and wind power in the Yukon mine in low discount rate scenarios - whereas previous sensitivity analyses have only incorporated wind power in this mine.
5. The elasticities of LCOE are the most sensitive in the Chilean and Australian off-grid mines whereas the elasticities of renewable penetration are the most sensitive in the Chilean grid-connected and the Yukon mines (see table 5.4 on page 158).

Interestingly, discount rates tend to vary significantly between public and private actors. Whereas public actors tend to apply a lower discount rate for investments that benefit the general public, private companies usually apply a much higher discount rate based on the opportunity cost of capital (Short et al., 2005). The opportunity cost of capital of mining companies was estimated to vary between 8% and 15% depending on commodity cycles (Engelhard, 2016). Even higher discount rates (i.e. risk-adjusted) can be applied for the most risky investments such as mining projects in countries with significant political risks. Based on the results of this study, it is clear that renewable technologies are at disadvantage when the discount rate is high. Low-risk financing schemes might help mitigating this issue and will be subsequently discussed in chapter 8 on page 213.

5.3.2.2 *Demand Shifting*

The sensitivity analysis on demand shifting explores the change of LCOE and technological mix associated with shifting the power demand of the mine at times when non-dispatchable renewable plants provide the highest output. The methodology for this analysis is provided in section 3.9.2 on page 75. Interestingly, very few studies have investigated the potential of demand shifting in mining (as discussed in 3.9.2 on page 75) but recent research published by a Chilean engineering company found that the demand flexibility of the mining industry is currently limited to a maximum of 10% of the demand for a few hours (Morales et al., 2015). Yet, further research is required to assess whether higher levels of demand-shifting can be realised.

Figure 5.16: LCOE and renewable penetration in relation to the demand-shifting of electricity

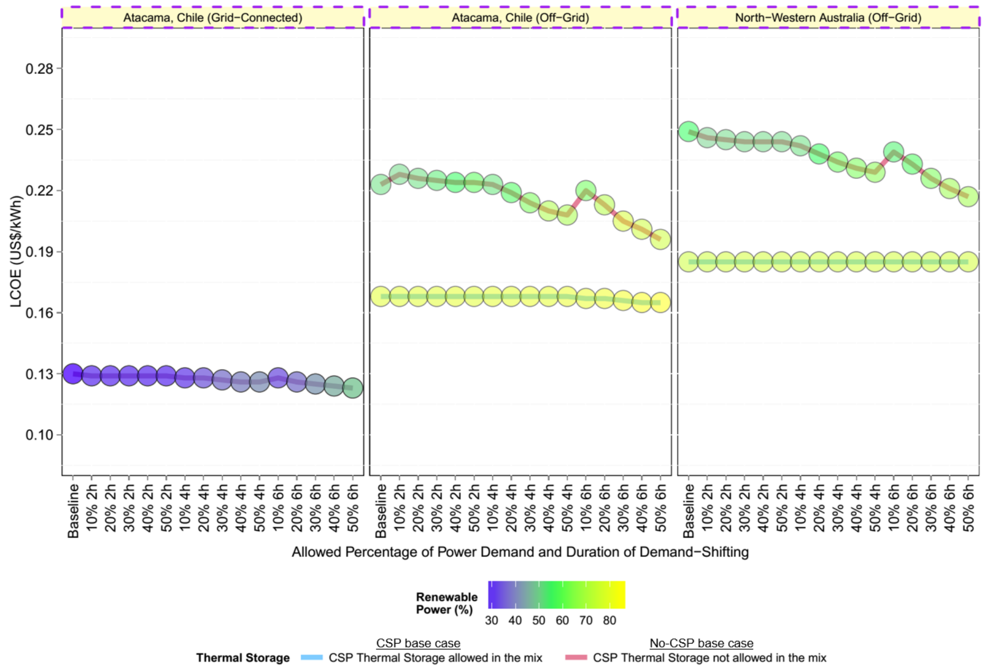
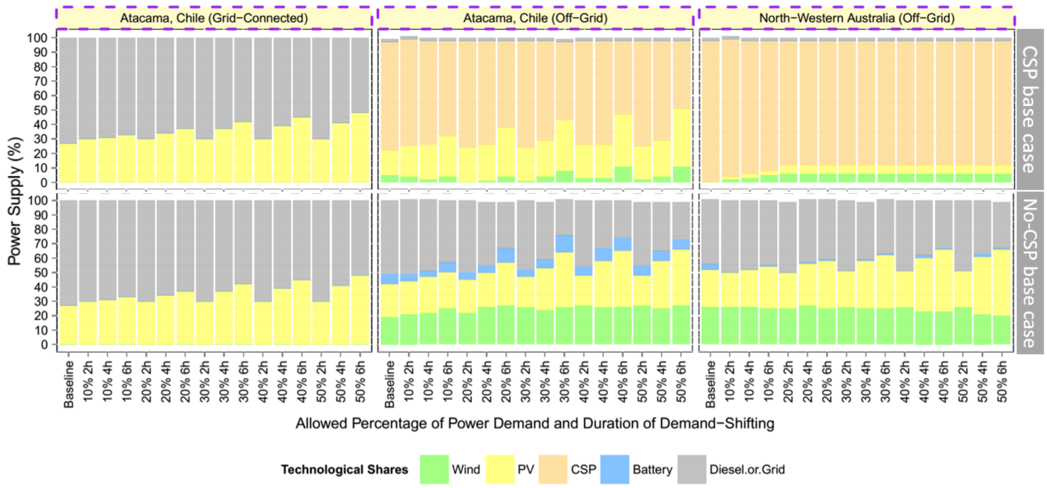


Figure 5.16 presents the variation of the LCOE with respect to the allowed percentage and duration of power demand to be shifted. In other words, the optimisation model is allowed to shift the load curve in this analysis and consequently optimise costs by oversizing the capacity of non-dispatchable technologies.

It can be observed that demand-shifting is only viable in the no-CSP base case, which features smaller amount of energy storage than the CSP base case. The elasticities of this analysis are close to zero for all mines (see table 5.4 on page 158). Further, the economic benefits of demand shifting are relatively limited with a maximum LCOE reduction of \$0.03/kWh in off-grid mines and \$0.01/kWh in the Chilean grid-connected mine. Figure 5.17 shows the evolution of each technological share in relation to different levels of demand shifting. Due to a lower cost per unit, the share of non-dispatchable power is increasing as more and more power demand is shifted. However, these results require more engineering and qualitative research to be validated. For instance, what is the impact of demand-shifting on the utilisation rate and variable cost of the mining equipment? Given that working patterns must be changed, is demand-shifting still a viable option? Those questions have to be answered by future research in order to value to the direct and indirect costs of demand-shifting.

Figure 5.17: Evolution of the optimal energy mix in relation to the demand-shifting of electricity

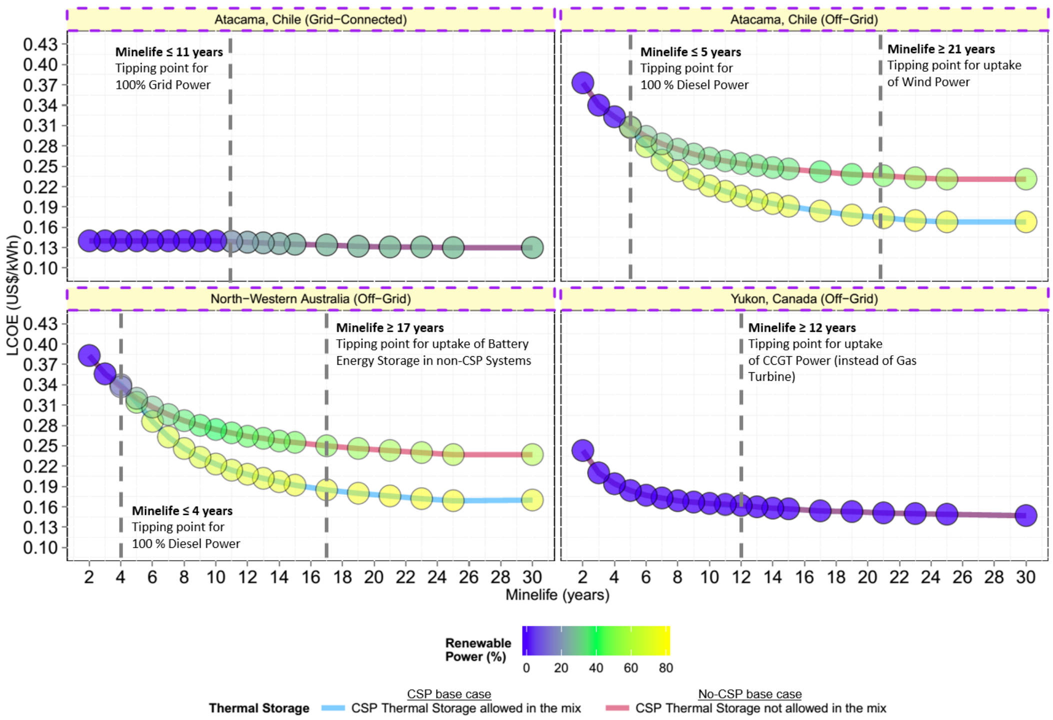


5.3.2.3 *Mine-life*

The sensitivity analysis on mine-life measures the change in LCOE, and technological mix for different investment periods. The results are presented in figure 5.18. Even though the mine-life periods of selected mines are relatively long i.e. between 17 and 25 years, the consideration of shorter investment periods is critical in an industry where plants can experience early shutdown or market exit in relation to changes in long-run commodity prices or policy changes (i.e. carbon taxation).

Results suggest that renewable technologies provide the highest economic return for long mine-life periods whereas fossil-fuel alternatives are the preferred generation option for shorter mine-life values. In the Australian and Chilean mines, the tipping point for using 100% of fossil-fuel is between 4 and 5 years in off-grid mines and 11 years in the Chilean grid-connected mine. There is positive uptake of PV power immediately above this threshold which illustrates its relatively short payback period. Other technologies have a longer payback periods with approximately 8 years for wind power and 17 years for battery storage in off-grid settings. Interestingly, there is no uptake of renew-

Figure 5.18: LCOE and renewable penetration as a function of the mine-life period (years)



able generation in the Yukon mine while varying mine-life periods. There is, however, a change of technological mix with CCGT being replaced by conventional gas turbines for mine-life periods equal or inferior to 12 years.

Another interesting outcome of this result is that the shape of the LCOE curve is relatively similar to an exponential distribution. This is a direct consequence of discounting future cash flows to the investment year. As a result, it can be observed that the LCOE curve is flattening down for mine-life periods superior to 12 years (with the exception of the grid-connected mine as there is no capital cost for grid power). The financial consequences associated with exiting the market are therefore diminished after this threshold.

Ultimately, the results of this analysis stress that different generation options involve different levels of risk. The most capitally intensive options might present a positive return on investment over the expected mine-life but could also generate significant losses if the investment period was to be significantly reduced.

A numerical characterisation of the risk associated with early market exit is investigated in chapter 7 on page 181 whereas a discussion on mine-life and geological uncertainty is provided in 8.2 on page 214.

5.3.3 *Impact of reducing capital costs*

In this section, the impact of future cost reductions on the LCOE and technological shares is presented for each renewable and storage alternatives. The last analysis of this section accounts for a combined cost reduction in all renewable and storage technologies (see 5.3.3.5 on page 147).

5.3.3.1 *Battery Cost*

The cost assumption for battery storage cost is $340/kWh in this study. This cost is declining at a rapid rate and is likely to be much lower in future years. A recent article of Nature Climate Change (Nykvist and Nilsson, 2015) stated that "industry-wide cost estimates [of battery] declined by approximately 14% annually between 2007 and 2014, from above US$1,000 per kWh to around US$410 per kWh, and that the cost of battery packs used by market-leading BEV manufacturers are even lower, at US$300 per kWh, and has declined by 8% annually. Learning rate, the cost reduction following a cumulative doubling of production, is found to be between 6 and 9%, in line with earlier studies on vehicle battery technology. [T]he costs of Li-Ion battery packs continue to decline and the costs among market leaders are much lower than previously reported."

Figure 5.19: Evolution of the optimal energy mix and LCOE in relation to battery cost

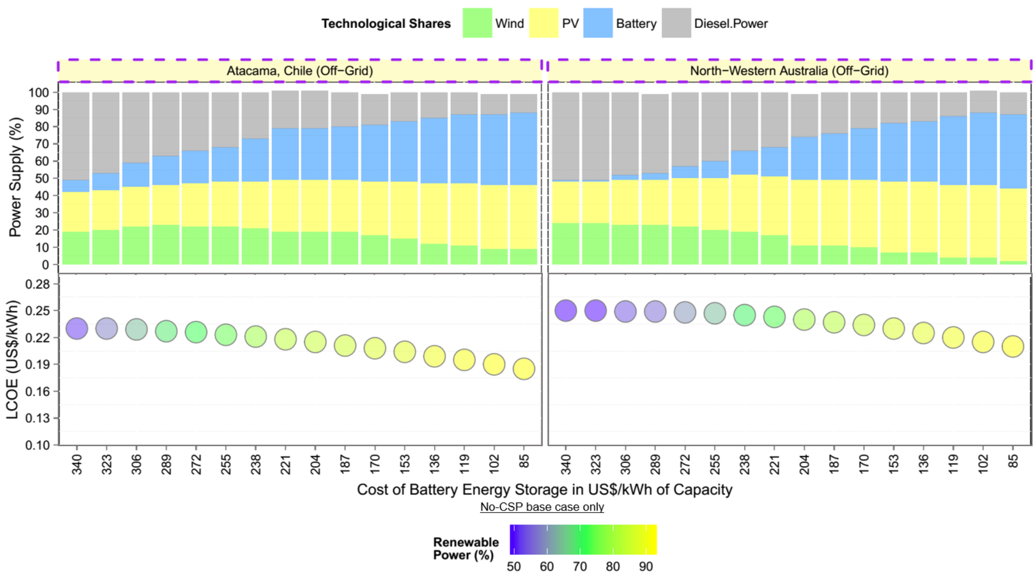


Figure 5.19 presents the impact of lower costs of battery capacity with respect to both the LCOE and renewable integration. A number of important caveats must be stated before commenting on the results of this analysis. First, the cost of the power converter

remains constant in this analysis as it is a relatively mature technology with little room for further cost reductions. Second, CSP power systems always feature a lower LCOE than the power systems of the no-CSP base case for all levels of battery cost presented in this sensitivity analysis - due to the significantly lower costs of CSP thermal storage (i.e. molten salt storage for CSP Tower is valued at $30/kWh-t or $71/kWh-e before heat decay losses) and the large amounts of energy storage required to supply continuous processes. Nevertheless, the future cost reductions of battery capacity might significantly diminish the gap between the cost of thermal storage and battery storage. Finally, there was no uptake of battery storage in both the Yukon mine and the Chilean grid-connected mine for all levels of cost reduction.

Despite these caveats, a number of observations can be derived from this sensitivity analysis on the no-CSP base case:

1. Lower levels of battery costs are directly associated with higher levels of renewable penetration - with an absolute increase of 40% of renewable penetration for battery costs at $100/kWh in both Australian and Chilean off-grid mines.
2. LCOE of Wind/PV/Battery power systems is situated between $0.18 and $0.21/kWh for battery costs of $100/kWh - hence reducing the gap between the LCOE of the CSP and no-CSP base cases to approximately 15%.
3. The LCOE of the battery plant itself is $0.36/kWh and $0.22/kWh (including input power from non-dispatchable sources) for battery costs at $340/kWh and $100/kWh respectively . Note that this LCOE could be substantially reduced for other applications that require more than one cycle of charging/discharging per day - therefore increasing the capacity factor and the energy output.

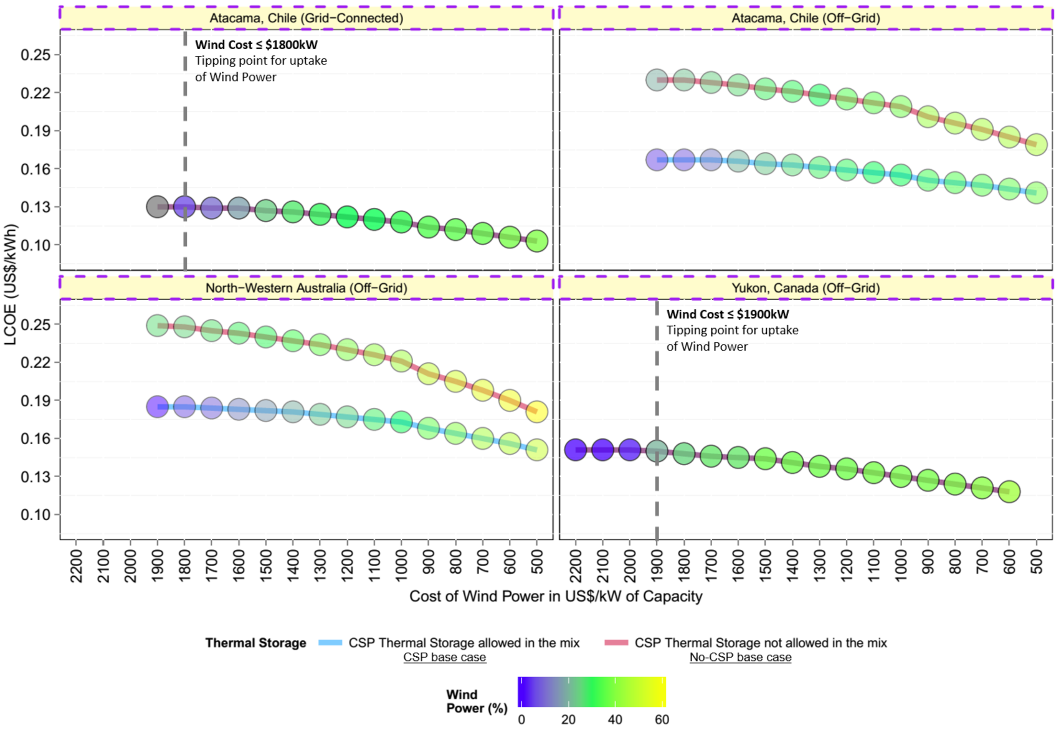
Interestingly, the battery market is currently more than doubling every year and battery costs are forecasted to reach $150/kWh by 2020 and $100/kWh by 2025 (Nykvist and Nilsson, 2015).

5.3.3.2 *Wind Cost*

The 5th assessment report of the IPCC (Victor et al., 2014) evaluated the cost of onshore wind power to be situated between $1200 and $3700/kW - the range of costs reflecting various sizes of wind projects. However, the economies of scale in wind projects were found to be relatively non-existent for power capacities over 20MW (Wiser, 2014) - which is the case in this research. The central cost assumption of this research accounts for a cost of $1900/kW in the Australian and Chilean mine for IEC class IIIs (Wiser et al., 2012). Capital costs for the Yukon mine are assumed to be $2200/kW due to the de-icing requirements (i.e. low temperature lubrication, heaters in inner blades, and ice detectors), and gear-less generator to reduce maintenance time as well as additional costs associated with icy climates (e.g. reinforced steel for temperature as low as -40C°). A review of the various de-icing technologies for wind projects is given in Parent and Ilinca (2011).

Other reports have published lower capital costs for wind power projects. For instance, Lazard (2014) presented a range of capital costs between $1400 and $1800/kW whereas the NREL annual technology baseline (2015) showed an average cost of $1800/kW. The impact of reducing the capital costs of wind power is subsequently presented in this sensitivity analysis. Figure 5.20 shows the change in LCOE and wind penetration for different levels of cost reduction.

Figure 5.20: LCOE of the power system as a function of wind cost

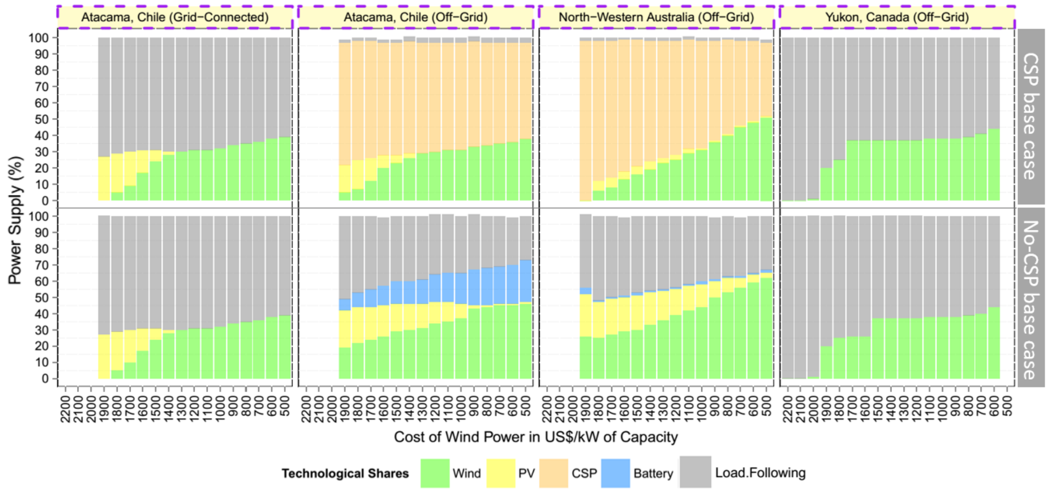


Key insights of this analysis are presented as follow:

1. There is a positive uptake of wind power at $1800/kW in the Chilean grid-connected mine and $1900/kW in the Yukon mine - hence presenting opportunities in the nearby area of the central cost scenarios for these mines.
2. The penetration of wind power reaches a significant share of the power supply at $1200/kW, i.e. 31% in the Chilean grid-connected mine, 30-34% in the Chilean off-grid mine, 37% in the Yukon mine, and 25-39% in the Australian off-grid mine.

3. As presented on the dispatch figure 5.21, wind power completely replaces PV power at 1300$/kW in the Chilean grid-connected mine and in the Chilean off-grid mine (CSP base case) - suggesting that current wind costs need to be reduced by 25% to entirely overtake PV power in these mines.
4. A reduction in wind capital costs is also associated with an increase uptake of battery storage in the Chilean off-grid mine (no-CSP base case) - which implies that lower capital costs in power generation have a significant impact on storage uptake (while storage costs remain constant).

Figure 5.21: Evolution of the optimal energy mix in relation to wind cost



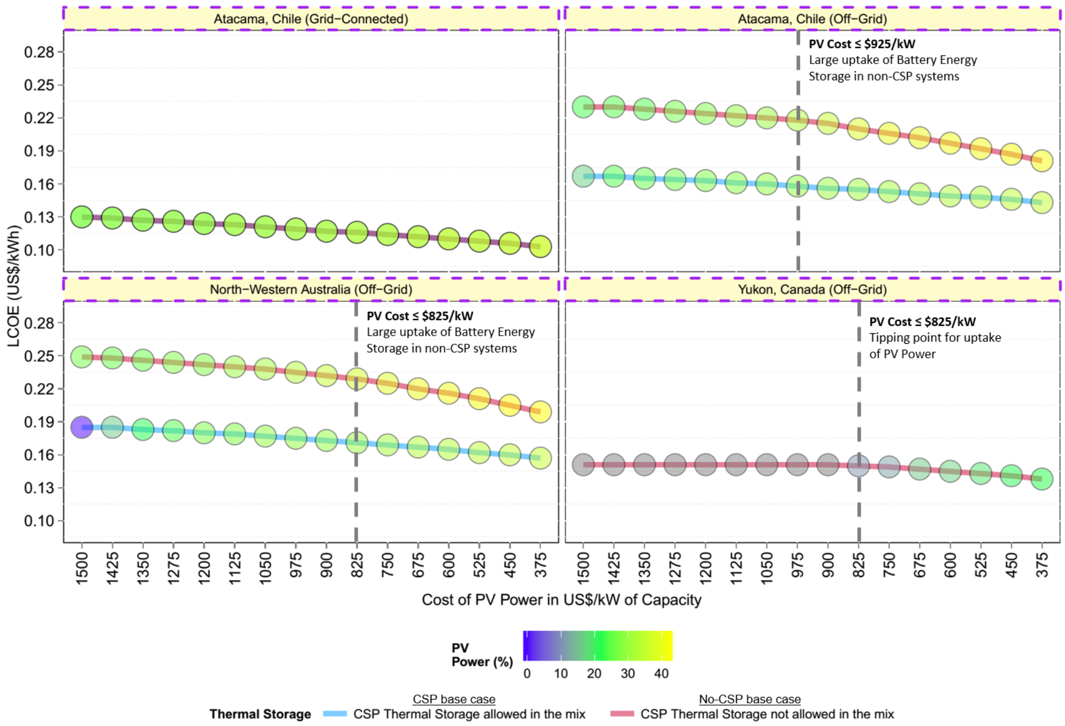
Note that this analysis is only accounting for changes in capital costs. The changes in wind speed will be investigated in chapter 6 on page 163 in the context of different climate scenarios.

5.3.3.3 *PV Cost*

The capital cost of PV power have declined substantially in the last 5 years. IEA (2012) presented costs of $4000/kW, IPCC (2014) used costs ranging between $1700 and $4300/kW for utility grade solar PV, and Lazard (2014) published cost estimates comprised between $1250 and $1750/kW. More recently, the capital costs of PV plants have further decreased with estimates at $1200/kW (Engelhard, 2016). A central scenario of $1500/kW was applied in this study - which was the best assumption at the time of the optimisation. A number of sensitivity analyses were performed to mitigate the uncertainty associated with PV capital costs and investigate the impact of future cost reductions.

Results provided in figure 5.22 present the evolution of the LCOE with respect to PV costs. Key observations are given as follow.

Figure 5.22: LCOE and PV uptake as a function of PV cost

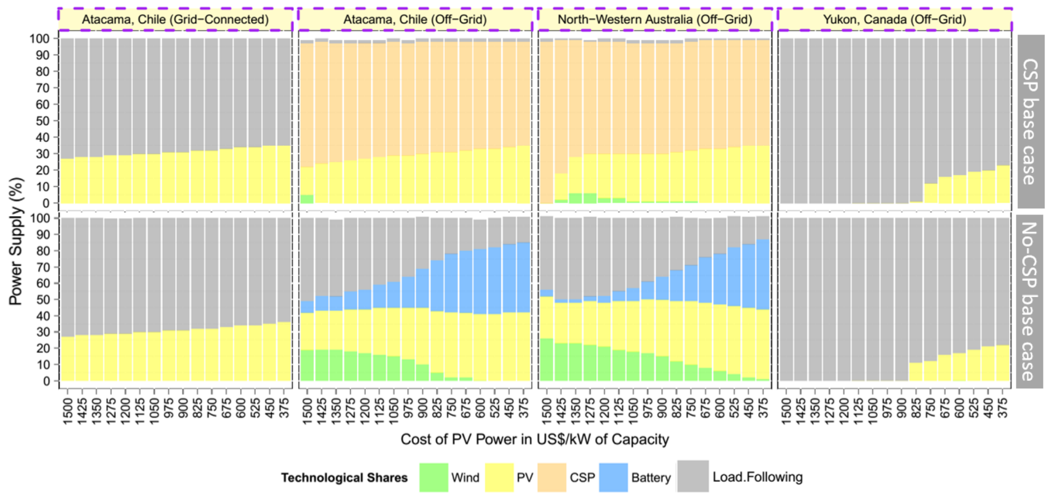


1. The LCOE of the Chilean grid-connected mine shows a substantial sensitivity to PV costs with a LCOE PV/Grid at $0.117/kWh (instead of $0.13/kWh) for capital costs at $975/kW - while increasing PV penetration from 27 to 31%.
2. PV power is included in the optimal mix of the Australian mine (CSP base case) for a reduction of 5% of PV capital costs.
3. As shown on figure 5.23 on the next page, there is a significant uptake of battery power associated with lower PV costs in both Australian and Chilean off-grid mines (no-CSP base case) - therefore emphasising the potential role of battery storage for renewable integration. Note that combined cost reductions for PV, wind, and battery are analysed in section 5.3.3.5 on page 147.
4. Interestingly, PV power also provides economic benefits in low irradiance climate (i.e. Yukon mine) for PV capital costs equal or below $825/kW - hence suggesting that future cost reductions in PV power could open new market areas.

5.3.3.4 *CSP Cost*

The total capital costs of CSP power systems include the cost of the solar field, power block, and thermal storage. The cost of these components is provided in chapter 4 on page 91 - based on NREL cost estimates (Turchi et al., 2010) and a recent research project carried out by the industrial partner of this PhD. Previous studies tend to provide

Figure 5.23: Evolution of the optimal energy mix in relation to PV cost

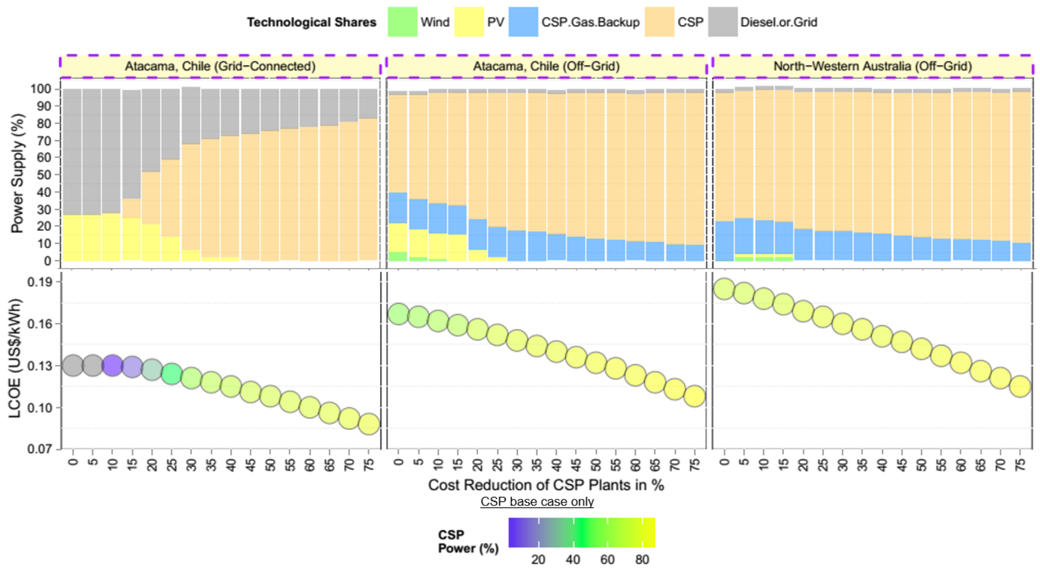


a cost per kW of capacity that sums-up the cost of all these components together. Due to the variety of CSP configurations in previous publications, such cost estimates are particularly difficult to interpret, due to various solar multiples (size of the solar field with respect to the size of the power block), tracking technologies (i.e. CSP tower with 2-axis tracking versus CSP parabolic trough with 1-axis tracking), use of gas-backup, and various sizes of thermal storage (i.e. from 0 to 20 hours of storage). For instance, IRENA (2012b) presented cost estimates ranging between \$4600 and \$10500/kW depending on tracking type and storage sizes. Similarly, Turchi et al. (2010) published costs situated between \$4600 and \$8000/kW for capacity factors ranging between 26% and 60% - leading to LCOE comprised between \$0.173 and \$0.10/kWh. Typically, the LCOE decreases with larger storage sizes, solar multiples, and capacity factors. For instance, the LCOE of a CSP tower system was estimated by Turchi et al. (2010) at \$0.14/kWh with 6 hours of storage and a 43% capacity factor; whereas a CSP tower with 12 hours of storage and a 60% capacity factor was valued at \$0.10/kWh.

The LCOE is slightly higher in this research (i.e. due to the higher discount rate) but is consistent with the results of past publications. Specifically, it was found that the LCOE of CSP tower in the Australian mine is situated between \$0.17 and \$0.19/kWh, with capacity factors around 60% with no gas-backup and 86% when combined with a gas-backup plant; whereas the LCOE in the Chilean mine is comprised between \$0.15 and \$0.17/kWh depending on capacity factors and uptake of gas-backup. Similarly, the cost per unit of generation capacity in HELiOS-Mining is consistent with previous studies with unit costs ranging between \$6000 and \$8000/kW.

Interestingly, EASAC (2011) presented a number of potential opportunities for future cost reductions in CSP power systems. For instance, there is a potential for a 25% cost reduction by using multi-tower systems, and efficiencies could be increased by 40-60% for higher operating temperatures. CSP tower presents the highest opportunities for efficiency gains with the implementation of a combined cycle process in the power block (+40/65% relative efficiency) whereas CSP parabolic trough can be further improved by using molten salt as heat transfer fluid (+20% relative efficiency). Similarly, Hinkley et al. (2013) suggest that 24.7% of the DNI is currently wasted in the CSP heat rejection cycle, and represents a significant opportunity for improvement. IRENA (2012b) assumes that between 28% and 40% of capital cost reduction could be achieved by 2020; and further states that CSP solar tower could become "the technology of choice in the future" as a consequence of technological improvements such as higher steam efficiency cycles and economies of learning on thermal storage.

Figure 5.24: Evolution of the optimal energy mix and LCOE in relation to CSP cost



In this context, this sensitivity analysis presents the impact of varying the capital cost on the LCOE of the power system. Figure 5.24 provides the results of this analysis. Two key insights can be drawn. First, there is a positive uptake of CSP power for cost reductions as low as 10% in the grid-connected Chilean mine - as well as relatively high elasticity values (see table 5.4 on page 158). Second, the share of CSP gas-backup power is decreasing as the cost reduction is increasing. Yet, there is a residual share of gas-backup at all cost levels due to the need to mitigate renewable intermittency throughout the year (e.g. consecutive cloudy days) and minimise the solar multiple. As a result, the gas-backup provides valuable capacity to accommodate daily and seasonal patterns of renewable intermittency and maintain appropriate levels of reliability.

5.3.3.5 *Cost of all renewable technologies*

This final sensitivity analysis measures the change in LCOE for a cost reduction on all renewable and storage technologies. Jansen et al. (2006) found a correlation coefficient of 0.5 between investment costs across the major types of generation plants (with no distinction between renewable and non-renewable sources). In this analysis, or thought experiment, it is assumed that there is a perfect correlation between future technological costs of renewable and storage plants. Yet, because this analysis is subdivided between the CSP and no-CSP base cases, the results can be interpreted in two ways. First, in the CSP base case, all technological costs are reduced in the same manner - hence showing how the LCOE and power mix are varying for a perfect cost correlation between all technologies. Second, in the no-CSP base case, the cost reduction is only applied to wind, PV, and battery storage - hence focusing the cost reduction on three renewable technologies.

Figure 5.25: LCOE and renewable uptake as a function of the cost of all renewable technologies

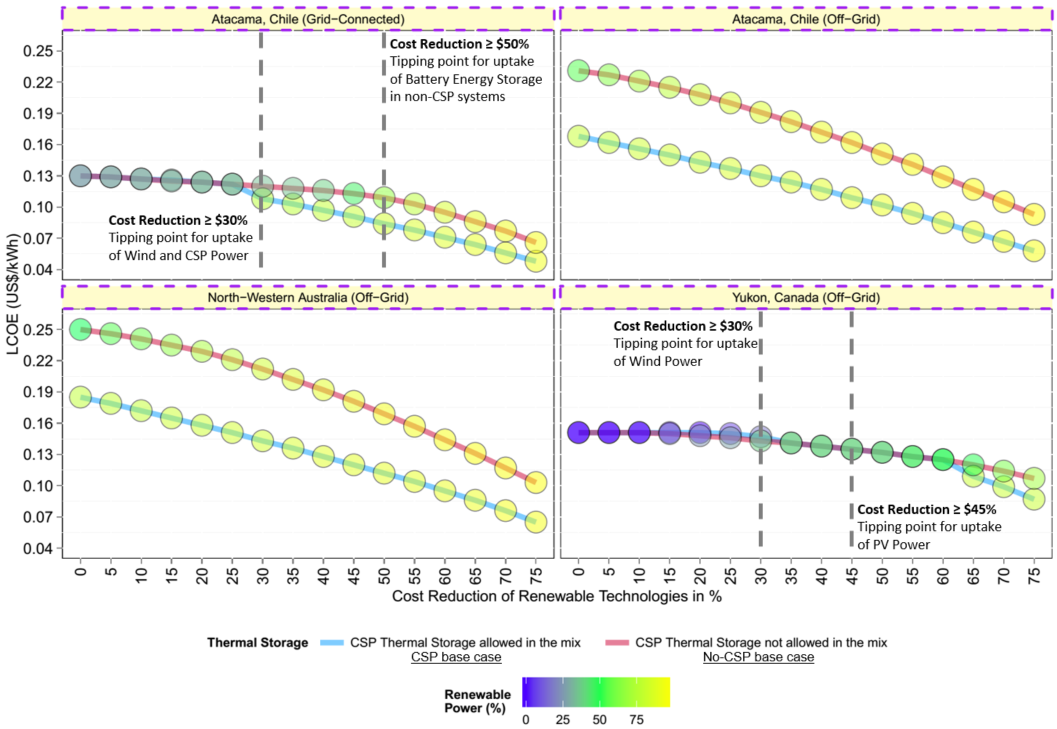
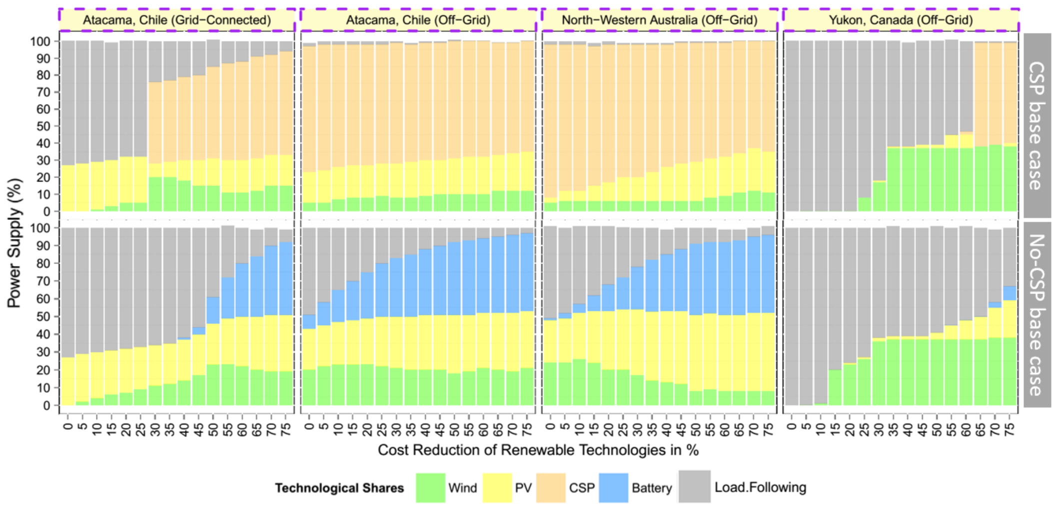


Figure 5.5 on page 119 presents the results of this sensitivity analysis. Key observations are provided as follow:

1. In the CSP base case, CSP power systems dominate the solution space in all mines. The impact of cost reductions is, however, different between CSP and no-CSP base cases. For instance, for a 75% cost reduction, the LCOE of the off-grid Chilean mine is reduced by 65% in the CSP base case and only 60% in no-CSP base case.
2. As shown in figure 5.26, the share of CSP power is decreasing in both Australian and Chilean off-grid mine for higher cost reductions - due to fuel switching between CSP gas-backup and non-dispatchable alternatives, i.e. wind, PV.
3. Whereas the share of renewable penetration is significantly increasing as cost is decreasing, there is a residual share of diesel generation in all scenarios so as to maximise the capacity factors of renewable plants. This phenomenon is further explored in the second research question in chapter 6 on page 163.

Figure 5.26: Evolution of the optimal energy mix in relation to a cost reduction on all renewable and storage technologies



5.4 IMPACT OF INPUT CHANGES IN RELATION TO FUTURE SCENARIOS

The results of all sensitivity analyses are compared in this section with regard to two future scenarios. Each of these scenarios is based on a range of independent input changes. As a result, the impact of each input change is assessed against changes in LCOE and renewable penetration for each variable. Ultimately, this analysis aims at determining the extent to which the optimal configurations given in table 5.3 on page 125 are robust from a system and economic standpoint. In other words, this section focuses on answering the following questions: Given that input parameters are uncertain, to what extent the optimal configurations of RQ1 present robust economic and technical characteristics? Which input parameters are the most influencing factors with respect to LCOE and renewable penetration?

In this context, the scenario A presents the relative impact of each parameter change for a realistic outlook (i.e. best-bet strategy) whereas the scenario B is focused on extreme values - based on the sensitivity analysis methodology given in Pannell (1997). The inputs values of these scenarios are based on assumptions of both the author and the industrial sponsor of this research as well as estimates from academic and market reports in scenario B. Comments about the robustness of the optimal technological configurations (as given in table 5.3 on page 125) are also given with respect to scenario A and B. The robustness of results is assessed in regard to both changes in LCOE and renewable penetration. It is assumed in this analysis that an optimal configuration is "robust" if each input change leads to an output change of less than 10%. Note that table 5.4 on page 158 provides a different view on input changes that does not consider scenarios but rather focuses on the sensitivity of each variable for a 1% input change (i.e. elasticities of LCOE and renewable penetration).

5.4.1 *Scenario A: Realistic outlook*

The realistic outlook refers to a scenario in which the value of several costs and input parameters have been changed based assumptions of the author and the industrial sponsor of this PhD in order to compare the impact of each variable change. While the choices of value in Scenario A are arbitrary (due to non-comparable units), they reflect a future that is consistent with current research and market studies (e.g. capital cost reduction of renewables, implementation of carbon policies, better financing conditions for clean-energy projects) as well as assuming small changes in mine-life, demand-shifting, and fuel prices. More sophisticated forecasting methods have been used to assess the risk associated with each technological configuration in chapter 7 on page 181 whereas the full range of variable changes has been given in previous sensitivity analyses. Despite these caveats, the comparison of different input changes provides useful insights on the influence of each input variable on the LCOE and the level of renewable penetration.

The following input values are considered in this scenario:

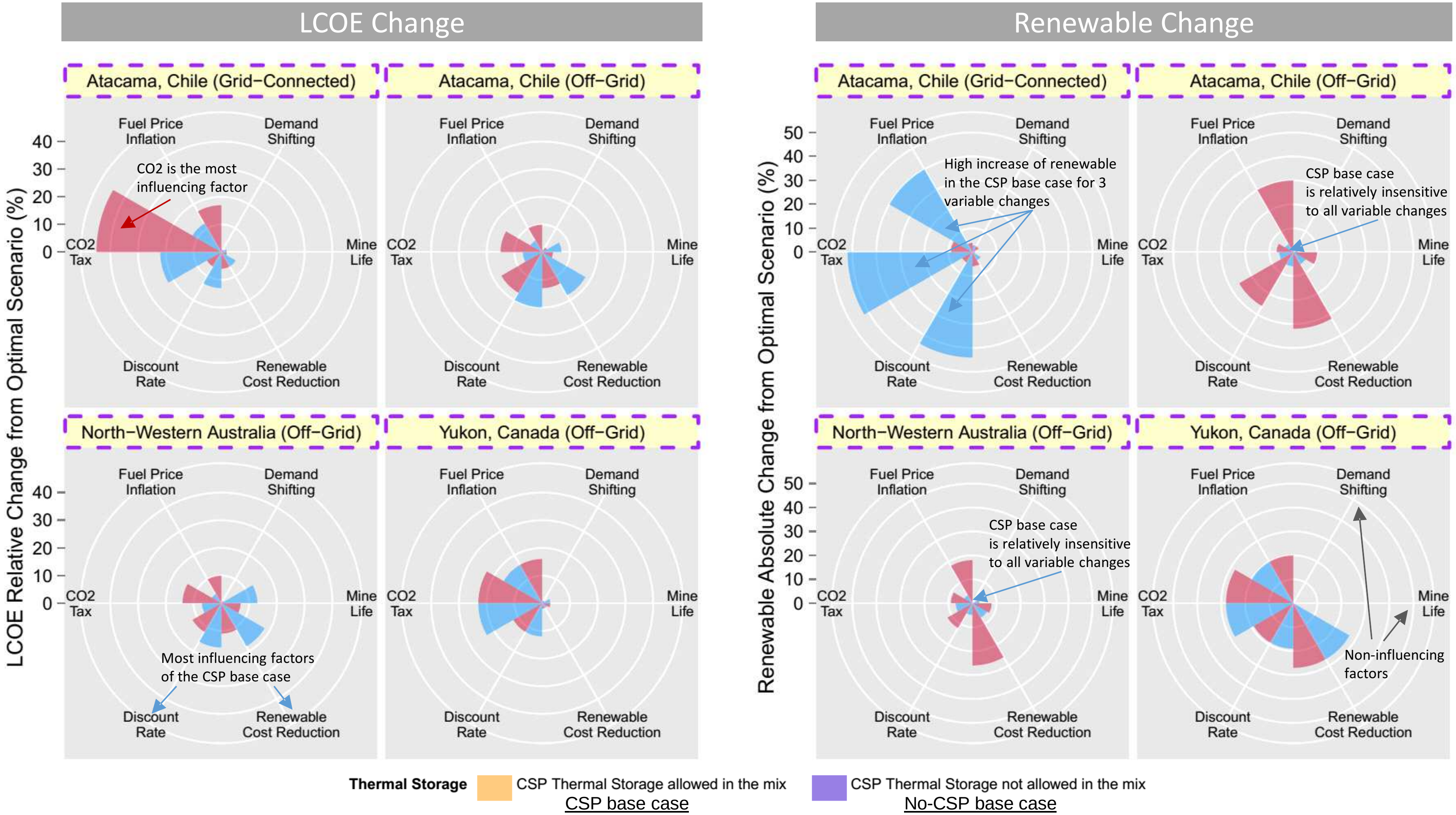
1. Carbon taxation = \$100/tCO_2 (instead of \$0/tCO_2)
2. Real fuel price change (fuel price inflation) = 2% year-on-year (instead of 0%)
3. Mine-life = 5 years shorter than the anticipated mine-life

4. Renewable cost = -25% from baseline costs
5. Nominal discount rate = - 4% from baseline (i.e. 12%)
6. Demand shifting = 20%, 2 hours/day (instead of 0%)

Figure 5.27 presents the impact of these input changes in relation to the LCOE and renewable penetration of the base cases - as given in table 5.3 on page 125. These results are given for both CSP and no-CSP base cases.

Note that all results have been converted to a sign-less value in order to present the relative strength of each input change. The following rule can be applied to ascertain the direction of each input change: the LCOE increases for criteria 1-3 and decreases criteria 4-6; the change in renewable penetration is positive for all criteria with the exception of mine-life. Interestingly, it was found that the impacts of input changes are relatively symmetrical with the exception of the mine-life criterion - due to the discounting of future cash flows (as discussed in section 5.3.2.3 on page 138).

Figure 5.27: Scenario A: Change of LCOE and renewable penetration from the optimal base cases in relation to realistic future scenarios



ATACAMA, CHILE (GRID-CONNECTED): The carbon taxation on fuel emissions is the most influential factor for both CSP and no-CSP base cases with respectively 22% and 45% LCOE increase. This level of carbon taxation is associated with a large uptake of renewable power in the CSP base case, i.e. +52%; whereas the share of renewable power only increases by 9% in the no-CSP base case, i.e. additional uptake of wind power to supplement existing PV capacity. Other major influencing factors include fuel price and discount rate.

Interestingly, the effects of these three input changes present similar outcomes: an uptake of CSP power associated with a large increase of renewable penetration in the CSP base case; and a small increase of non-dispatchable renewables in the no-CSP base case.

Based on these results, it can be concluded that the power mix of the CSP base case varies significantly with three out of six input changes and is therefore not characterised as robust from a system standpoint. This outcome is consistent with the strength and direction of the elasticity values given in table 5.4 on page 158. On the contrary, the power mix of the no-CSP base case presents more robust characteristics due to its relatively insensitivity to the input changes of this scenario (the concept of robustness is defined in the preamble of this section in 5.4 on page 148).

Note that more sophisticated analyses are performed in the following chapters in order to further test the robustness of optimal power configurations - i.e. statistical forecasting of fuel prices in 7.2.1 on page 185, semi-variance analysis of mine-life in 7.3.2 on page 192, and scenario-based analysis of future carbon prices in 7.3.3 on page 195.

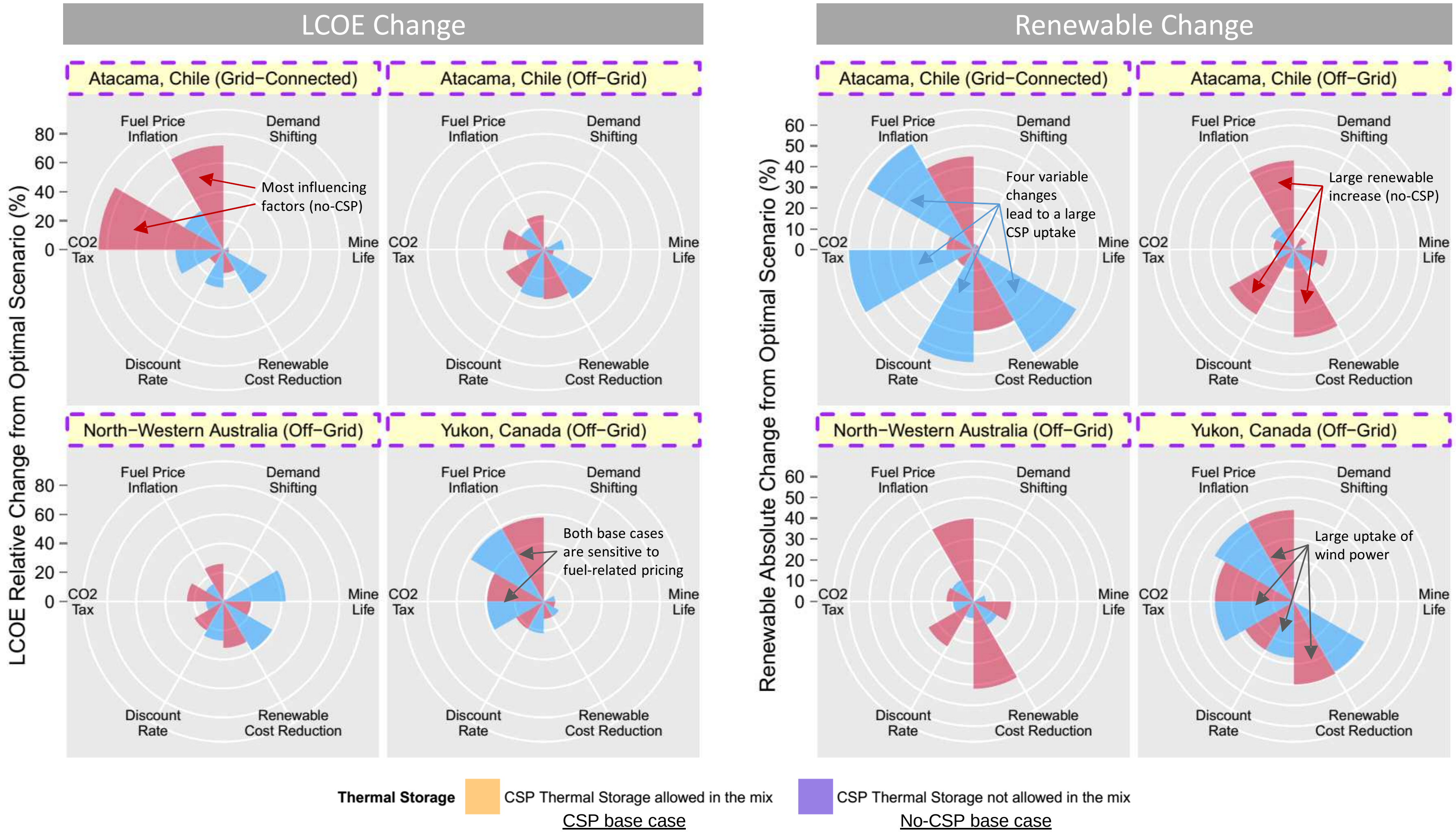
OFF-GRID CHILEAN AND AUSTRALIAN MINES: The two largest influencing factors for both mines are the discount rate and the cost reduction of renewable/storage technologies in the CSP base case - reducing the LCOE by an average of 18%. Yet, these changes have a negligible impact on renewable penetration - with an average absolute increase of 6%. On the contrary, in the no-CSP base case, the change of discount rate and capital cost are associated with a significant change in renewable penetration - with an average absolute increase of 24%; whereas the LCOE is reduced by an average of 13% for these criteria. Finally, the change in carbon taxation is ranked second in the Chilean mine and first in the Australian mine for non-CSP systems - with a large LCOE change (i.e. 15%) and a relatively small change in renewable uptake (i.e. 8%).

Ultimately, because the economic optima of the CSP base case include large renewable capacities, there is little room for additional renewable capacities and reductions of carbon emissions. In other words, the scenario A of the CSP base case is relatively insensitive to input changes in terms of renewable capacity - and can be considered as robust from an energy mix standpoint. On the other hand, the power mix of the no-CSP base case is relatively sensitive to discount rate, carbon taxation, and capital cost - hence suggesting that these criteria should be taken into account by decision-makers (see decision-analysis in 7.4 on page 197).

yukon, canada (off-grid): Three factors were found to significantly influence the LCOE of the power system: carbon taxation, fuel price inflation, and discount rate. All of these factors are directly associated with an uptake of wind power situated between 19% and 28% of the power supply. Interestingly, the cost reduction criterion is associated with the largest uptake of wind power (i.e. 27%). There are no economic optima that include CSP plants in this mining context due to the relatively low solar irradiance.

Finally, this result suggests that the least-cost power system based on CCGT power is not robust from a system standpoint. A change in four out of six criteria directly leads to an uptake of significant wind capacities in the power mix. This outcome is consistent with the high elasticity values that were found for this mine - see table 5.4 on page 158.

Figure 5.28: Scenario B: Change of LCOE and renewable penetration from the optimal base cases in relation to extreme future scenarios



5.4.2 *Scenario B: Extreme values*

More extreme input changes are hypothesised in this scenario. Specifically, a carbon price of \$200/tCO_2 is assumed, as per the recommendations of IPCC (2011) and Rivers (2014). Second, the mine closes ten years earlier than expected due to low commodity prices or a higher depletion rate - see discussion in 8.2 on page 214. Third, the capital costs of renewable technologies are 50% lower than the central cost scenario - see section 5.3.3 on page 140 for more details on future cost reductions. Fourth, the real fuel costs increases 7% year on year - hence assuming significant supply shortages on fuel markets (see portfolio chapter for more details in 7.2.0.1 on page 184). Fifth, the discount rate is set at 5% (instead of 12%) - reflecting a very low financing and risk premium rate (as discussed in 8.4 on page 219). Finally, this scenario hypothesises that 50% of the power demand can be shifted for two hours per day - hence assuming that there is significant process re-engineering that can be performed to viably achieve high levels of demand-shifting (see 5.3.2.2 on page 137). Again, all of the above-stated input changes were not performed simultaneously. Instead each input change was performed independently in order to identify the most influencing factors.

A number of observations on the results of this scenario are given as follows - and presented in 5.28. Note that the scales of this figure are different than the scales in scenario A - due to large variations of LCOE and renewable penetration.

ATACAMA, CHILE (GRID-CONNECTED): In the CSP base case, four input variables have a significant impact on the LCOE, including: renewable cost reduction, carbon taxation, fuel price inflation, and discount rate - with a change of 35%, 33%, 31%, and 26% respectively. These factors are also associated with an increase of renewable capacity of 54% to 60%. The input factors mine-life and demand shifting have little or no impact on both the LCOE and the renewable capacity, i.e. 1-4%.

In the no-CSP base case, there are two input variables significantly associated with LCOE change, including: carbon taxation and fuel price inflation - with a change of 86% and 72% respectively. Further, two input changes have a significant impact on the power mix: fuel price inflation, and renewable cost reduction with an absolute change in renewable penetration of 45% and 39% respectively.

Overall, it is argued that the power mix of both CSP and no-CSP base cases are sensitive to extreme changes in input parameters for four criteria: renewable cost reduction, carbon taxation, fuel price inflation and discount rate (whereas demand-shifting and mine-life have negligible impacts). This sensitivity analysis hence suggests that there are economic risks associated with the optimal mixes of this mine in case of extreme input changes. Yet, the no-CSP base case presents a much higher sensitivity to input changes than the CSP base case - due to different shares of renewable resources in the mix. As a result, the higher share of renewable resources of the CSP base case contributes to a significant reduction of the risk associated with extreme events. The third research question will consider these risks in relation to decision-analysis and portfolio theory in chapter 7 on page 181.

OFF-GRID CHILEAN AND AUSTRALIAN MINES: In the CSP base case, five input variables have a significant impact on the LCOE, including: renewable cost reduction, discount rate, fuel price inflation, mine-life, and carbon taxation - with changes of 39%, 27-33%, 14-18%, 14-43%, and 12% respectively. Despite large LCOE changes, these input changes are associated with small changes in the power mix, i.e. between 4% and 13%. Interestingly, these changes are relatively similar across both mines except for the mine-life - due to the non-linear nature of the LCOE for different mine-life periods as discussed in section 5.3.2.3 on page 138.

In the no-CSP base case, the same five factors are significantly influencing the LCOE - with changes between 19% and 34%. However, the renewable penetration does largely vary in this base case - with up to 42% additional renewable capacity for a 50% reduction in renewable and storage costs.

Overall, it was found that the CSP base case presents robust results in terms of optimal power mix (i.e. low sensitivity as defined in 5.4 on page 148) whereas the power mix of the no-CSP base case varies significantly with the input changes of the scenarios B - due to the higher sensitivity of large shares of fuel-based power in the no-CSP base case. This outcome implies that different perspectives on future input parameters could lead to different optimal solutions for the no-CSP base case - which will be further analysed in chapter 7 on page 181.

YUKON, CANADA (OFF-GRID): In both base cases, four criteria were found to have a significant impact on both the LCOE and the renewable penetration, namely fuel price inflation, carbon taxation, discount rate, and renewable cost reduction. These changes are associated with significant uptake of wind capacity and raise the share of renewable energy by up to 44%. Implementation of demand shifting and changes in mine-life have a negligible impact on the LCOE and no impact on the uptake of renewable power.

As a result, the optimal base case of the Yukon mine was found to be sensitive to extreme input changes, which might lead to significant economic risk if one of these extreme changes was to materialise. A decision-analysis is subsequently conducted in section 7.4 on page 197 in order to further analyse the solution space associated with relevant input changes.

5.5 SUMMARY

This chapter has provided a techno-economic characterisation of cost optimal hybrid power systems for four mining contexts. It conclusively demonstrates that there are opportunities for reducing carbon emissions while increasing economic competitiveness at the same time. Specifically, it was found that carbon emissions can be reduced by 27-82% while generation costs can be reduced by 7-57% depending on context-specific characteristics (see table 5.1 on page 114). Further carbon reductions have been identified in the various sensitivity analyses (summarised in table 5.5 on page 160) with respect to future fuel costs, capital costs, and mining characteristics.

Selected key outcomes of this chapter are summarised below (while all key findings are restated in the conclusion of the thesis in chapter 9 on page 229):

- A residual share of fuel-based power generation was found to remain in the optimal mix for all input changes of all sensitivity analyses. This outcome stresses that fossil-fuel generation provides valuable capacity to accommodate daily and seasonal patterns of renewable intermittency as well as maintains appropriate levels of reliability. Chapter 6 on page 163 further investigates this finding with respect to the value of lost load.
- CSP power plants dominate the solution space for two out of four mining contexts. This finding is directly associated with the cost of storage capacity. Because mining activities have a constant power demand, there is a need for large amounts of energy storage in order to maximise the uptake of low-cost intermittent renewable resources and provide a constant power supply. This finding is likely to be different for other contexts where the power demand is subject to peak/off-peak variations (e.g. residential load). Yet, CSP plants are the most capital intensive alternatives,

Table 5.4: Elasticities of input changes

Analysis	Elasticity	CSP base case: Atacama, Chile (grid-connected)	CSP base case: Atacama, Chile (off-grid)	CSP base case: Yukon, Canada (off-grid)	CSP base case: North-Western Australia (off-grid)	No-CSP base case: Atacama, Chile (grid-connected)	No-CSP base case: Atacama, Chile (off-grid)	No-CSP base case: Yukon, Canada (off-grid)	No-CSP base case: North-Western Australia (off-grid)
Fuel Prices									
LNG Price	*LCOE*		0.23	0.51	0.24			0.51	
	Renewable penetration		0.18	2.33	0.25			2.33	
Diesel Price	*LCOE*		0.04	0.21	0.04		0.41	0.21	0.49
	Renewable penetration		0.07	1.86	0.09		0.89	1.86	0.86
Grid Price	*LCOE*	0.52				0.78			
	Renewable penetration	1.85				0.61			
Grid Capacity firming	*LCOE*	0.05				0.01			
	Renewable penetration	0.33				0.07			
Fuel Price Inflation	*LCOE*	0.23	0.11	0.33	0.09	0.39	0.18	0.33	0.19
	Renewable penetration	1.19	0.12	2.50	0.12	0.30	0.58	2.50	0.65
Carbon Taxation	*LCOE*	0.10	0.03	0.10	0.03	0.18	0.07	0.10	0.06
	Renewable penetration	0.49	0.04	1.00	0.04	0.14	0.06	1.00	0.08
Mine Characteristics									
Discount Rate	*LCOE*	0.29	0.60	0.37	0.48	0.18	0.47	0.38	0.38
	Renewable penetration	-1.55	-0.25	-2.58	-0.27	-0.54	-1.14	-3.00	-0.56
Demand Shifting	*LCOE*	-0.01	0.00		-0.02	-0.01	-0.08		-0.05
	Renewable penetration	0.09	-0.02		0.04	0.09	0.43		0.17
Minelife	*LCOE*	-0.08	-0.26	-0.09	-0.25	-0.08	-0.12	-0.09	-0.14
	Renewable penetration	0.22	0.12	0.00	0.10	0.21	0.76	0.00	0.53
Capital Costs									
Battery Cost	*LCOE*						0.16		0.10
	Renewable penetration						-0.75		-0.78
Wind Cost	*LCOE*	0.16	0.12	0.17	0.12	0.16	0.17	0.17	0.20
	Renewable penetration	-0.28	-0.05	-4.00	-0.07	-0.28	-0.53	-4.00	-0.12
PV Cost	*LCOE*	0.20	0.13	0.02	0.13	0.20	0.16	0.02	0.15
	Renewable penetration	-0.27	-0.03	-3.00	-0.07	-0.27	-0.71	-3.00	-0.44
CSP Cost	*LCOE*	0.28	0.35		0.40				
	Renewable penetration	-1.43	-0.09		-0.16				
All Renewable & Storage Cost	*LCOE*	0.64	0.73	0.20	0.74	0.27	0.63	0.20	0.58
	Renewable penetration	-1.53	-0.21	-3.00	-0.21	-1.25	-0.80	-3.00	-0.95

which implies that variations in mine-life values are of great significance (see 7.3.2 on page 192 for a risk analysis of the mine-life criterion).

- Input parameters have higher elasticity values in the Chilean grid-connected mines and the off-grid Canadian mine (as shown in table 5.4). Most elastic values for these mines have been found to be associated with fuel prices, discount rate, and reduction of capital costs. On the contrary, the Chilean and Australian off-grid mines are characterised by less sensitive solutions based on CSP plants complemented by fossil-fuel and non-dispatchable resources. The input changes associated with demand-shifting was found to negligibly impact the LCOE and the amount of renewable resources in all mines. Chapter 7 on page 181 further investigates the sensitivity of key input variables in a portfolio framework.
- Future scenario analyses have shown that larger shares of renewable resources are hedging off the risk associated with future fuel price variations. Power systems with smaller shares of renewable resources are much more sensitive to variations in fuel and carbon prices. This outcome means that different perspectives on future prices and carbon policies might lead to widely different solutions. Subsequently,

section 7.4 on page 197 will take into consideration these different perspectives in a decision-analysis framework.

The following chapter provides an enhanced view on the results of this chapter with respect to reliability considerations. A brief summary of the tipping points identified in previous sensitivity analyses is given as follows.

Table 5.5: Tipping points for further carbon reductions from base cases

	Parameters	Atacama, Chile (Grid-Connected)					Atacama, Chile (Off-Grid)					Yukon, Canada (Off-Grid)					North-Western Australia (Off-Grid)				
			Change of Carbon Emitted from base cases					Change of Carbon Emitted from base cases					Change of Carbon Emitted from base cases					Change of Carbon Emitted from base cases			
		Value in the Optimisation Model	*-10%*	*-25%*	*-50%*	*-75%*	*Value in the Optimisation Model*	*-10%*	*-25%*	*-50%*	*-75%*	*Value in the Optimisation Model*	*-10%*	*-25%*	*-50%*	*-75%*	*Value in the Optimisation Model*	*-10%*	*-25%*	*-50%*	*-75%*
CSP base case	**Fuel Prices**																				
	Diesel						$0.85/l.	≥$3/l.				$1/l.	≥$1.5/l.	≥$2/l.			$1.03/l.				
	Grid Power	$0.14/kWh		≥$0.15/kWh		≥$0.16/kWh															
	Natural Gas	$20/MMbtu					$20/MMbtu		≥$25/MMbtu	≥$30/MMbtu		$12/MMbtu		≥$15/MMbtu	≥$18/MMbtu		$20/MMbtu		≥$25/MMbtu		≥$30/MMbtu
	Nominal Fuel Inflation	3%/y.			≥4%/y.	≥5%/y.	3%/y.	≥4%/y.	≥5%/y.	≥6%/y.	≥8%/y.	3%/y.		≥5%/y.	≥6%/y.		3%/y.	≥4%/y.	≥6%/y.	≥8%/y.	≥9%/y.
	Carbon Taxation	$0/t		$40/t	$50/t	$120/t	$0/t	$20/t	$80/t	$200/t		$0/t	$50/t	$80/t			$0/t	$30/t	$80/t	$200/t	
	Mine Characteristics																				
	Minelife	25y.					25y.					22y.					17y.	≥21y.			
	Demand-Shifting (%, duration)	0%, 0h.	30%, 4h.	30%, 6h.			0%, 0h.	30%, 4h.	30%, 6h.			0%, 0h.					0%, 0h.				
	Nominal Discount Rate	12%				≤9%	12%	≤10%	≤9%	≤7%	≤5%	12%		≤8%	≤3%		12%	≤10%	≤8%	≤5%	≤3%
	Capital Costs (coefficient)																				
	PV	100%	≤30%				100%	≤50%				100%	≤55%	≤30%			100%	≤80%	≤25%		
	Wind	100%	≤35%				100%	≤70%	≤30%			100%		≤85%	≤75%	≤25%	100%				
	CSP	100%	≤85%		≤80%	≤75%	100%	≤60%	≤55%	≤40%	≤25%	100%					100%	≤75%	≤60%	≤45%	≤25%
	CSP, PV, and Wind	100%				≤75%	100%	≤90%	≤80%	≤70%	≤60%	100%		≤85%	≤75%	≤45%	100%	≤90%	≤80%	≤65%	≤60%
No-CSP base case	**Fuel Prices**																				
	Diesel						$0.85/l.		≥$0.9/l.	≥$1/l.	≥$1.1/l.	$1/l.	≥$1.5/l.	≥$2/l.			$1.03/l.		≥$1.1/l.	≥$1.2/l.	≥$1.3/l.
	Grid Power	$0.14/kWh	≥$0.21/kWh	≥$0.25/kWh		≥$0.30/kWh															
	Natural Gas	$20/MMbtu					$20/MMbtu					$12/MMbtu		≥$15/MMbtu	≥$18/MMbtu		$20/MMbtu				
	Nominal Fuel Inflation	3%/y.	≥7%/y.		≥9%/y.	≥10%/y.	3%/y.		≥4%/y.		≥5%/y.	3%/y.		≥5%/y.	≥6%/y.		3%/y.	≥4%/y.		≥5%/y.	≥6%/y.
	Carbon Taxation	$0/t	$70/t	$200/t			$0/t	$70/t	$160/t			$0/t	$50/t	$80/t			$0/t	$50/t	$100/t		
	Mine Characteristics																				
	Minelife	25y.					25y.					22y.					17y.	≥23y.			
	Demand-Shifting (%, duration)	0%, 0h.	20%, 4h.	30%, 6h.			0%, 0h.	20%, 4h.	30%, 4h.			0%, 0h.					0%, 0h.				
	Nominal Discount Rate	12%	≤6%	≤4%			12%		≤10%	≤9%	≤8%	12%		≤8%	≤3%		12%	≤10%	≤8%	≤6%	≤5%
	Capital Costs (coefficient)																				
	PV	100%	≤30%				100%	≤80%	≤70%	≤60%	≤55%	100%	≤55%	≤30%			100%	≤75%	≤65%	≤55%	≤50%
	Wind	100%	≤45%				100%	≤85%	≤70%	≤40%	≤25%	100%		≤85%	≤75%	≤25%	100%	≤75%	≤55%	≤25%	
	Battery	100%					100%	≤90%	≤85%	≤75%	≤70%	100%	≤45%	≤30%			100%	≤85%	≤75%	≤65%	≤60%
	PV, Wind, and Battery	100%	≤70%	≤55%		≤50%	100%	≤95%	≤90%	≤85%	≤80%	100%		≤85%	≤75%	≤45%	100%	≤90%	≤85%	≤80%	≤75%

5.5.1 *Tipping points of sensitivity analyses*

Table 5.5 on the preceding page provides a summary of the tipping points for each variable of the sensitivity analyses. These results are given for four levels of carbon reduction from base cases: 10, 25, 50, and 75%. Given that the CSP base case is associated with larger levels of carbon reduction against grid/diesel power baselines (as detailed in table 5.3 on page 125), these tipping points tend to be significantly different between the CSP and no-CSP base cases. Key observations are given as follow for carbon reductions equal or above 50% from base cases.

5.5.1.1 *CSP base case*

- In the Chilean grid-connected mine, six variable changes are associated with a reduction of 50% or more of carbon emissions: grid prices of $0.16/kWh (instead of $0.12/kWh), nominal year-on-year fuel price increase of 5% (instead of 3%), carbon price at $50/t (instead of $0/t), discount rate at 9% (instead of 12%), and capital cost reduction of CSP plants or all renewable/storage technologies of 25%. Most of these variable changes imply that the CSP configuration with higher shares of renewable power becomes economical and hence replaces or complements the PV/Grid alternative - therefore significantly reducing indirect grid emissions.
- In the Chilean off-grid mine, seven variable changes lead to 50% or more carbon reduction: LNG prices at $30/MMBTU (instead of $20/MMBTU), nominal year-on-year fuel price increase of 6% (instead of 3%), carbon price at $200/t (instead of $0/t), discount rate at 7% (instead of 12%), CSP capital cost reduction of 60%, and capital cost reduction of all renewable/storage technologies of 30%. These changes are associated with a share reduction of the CSP gas-backup and diesel power along with additional PV and wind capacities in the mix.
- In the Yukon off-grid mine, five variable changes are associated with a reduction of 50% or more of carbon emissions: LNG prices at $18/MMBTU (instead of $12/MMBTU), nominal year-on-year fuel price increase of 6% (instead of 3%), discount rate at 3% (instead of 12%), and capital cost reduction of wind power of 25%. All changes are associated with an uptake of wind power and a lower share of diesel power. These tipping points are identical for the no-CSP base case.
- In the Australian off-grid mine, six variable changes lead to a 50% or more carbon reduction: LNG prices at $30/MMBTU (instead of $20/MMBTU), nominal year-

on-year fuel price increase of 9% (instead of 3%), carbon price at $200/t (instead of $0/t), discount rate at 5% (instead of 12%), CSP capital cost reduction of 55%, and capital cost reduction of all renewable/storage technologies of 35%. Similarly to the Chilean off-grid mine, these changes are associated with lower shares of CSP gas-backup and diesel power and higher shares of PV and wind power in the mix.

5.5.1.2 *No-CSP base case*

- In the Chilean grid-connected mine, three variable changes are associated with a reduction of 50% or more of carbon emissions: grid prices of $0.30/kWh (instead of $0.12/kWh), nominal year-on-year fuel price increase of 9% (instead of 3%), and capital cost reduction of all renewable/storage technologies of 50%. Most of these variable changes involve additional PV and wind capacities along with an uptake of battery storage - hence significantly reducing indirect fuel-based emissions from the grid.
- In the Chilean off-grid mine, seven variable changes are associated with a reduction of 50% or more of carbon emissions: diesel prices of $1/l. (instead of $0.85/l), nominal year-on-year fuel price increase of 5% (instead of 3%), discount rate at 9% (instead of 12%) as wells as capital costs of PV reduced by 40%, wind by 60%, battery storage by 25%, and all renewable/storage technologies by 15%. Most of these variable changes involve more PV and wind in the mix along with additional battery storage capacities - hence significantly reducing fuel-based emissions from the diesel plant.
- In the Australian off-grid mine, seven variable changes are associated with a reduction of 50% or more of carbon emissions: diesel prices of $1/2. (instead of $0.85/l), nominal year-on-year fuel price increase of 5% (instead of 3%), discount rate at 6% (instead of 12%) as well as capital costs of PV reduced by 45%, wind by 75%, battery storage by 35%, and all renewable/storage technologies by 20%. Similarly to the Chilean off-grid mine, these variable changes imply additional PV, wind, and battery capacities in the mix.

6

RELIABILITY COSTS

In this chapter, the results from the previous chapter have been enhanced in order to account for reliability considerations. The aim of this chapter is to understand the trade-off between the cost and benefit of different reliability levels. In this respect, the research question that is considered in this chapter is the following: What is the optimal trade-off between capacity cost and reliability cost?

This chapter is structured as follows. The first section provides some background on the climate data that are used in the adequacy analysis. In the second section, a numerical characterisation of the value of lost load is performed in relation to the cost of foregone production. The third section provides the results of the adequacy optimisation for all cost optimal hybrid power systems of research question one (RQ1). In section four, two sensitivity analyses are performed in relation to changes in the value of foregone production as well as different constraints on the energy index of reliability (EIR). Finally, the last section of this chapter summarises the results and key takeaways of the adequacy analysis.

6.1 CLIMATE DATA FOR WORST CASE CLIMATE SCENARIOS

Because of the intermittent nature of renewable resources, a critical aspect in designing hybrid renewable power systems is the reliability of supply (Kashefi Kaviani et al., 2009). Accordingly, an adequacy analysis is provided in this chapter in order to measure the impact of different levels of intermittency on reliability coefficients. Whereas the sources of selected climate datasets were given in the data chapter 4 on page 91, further background explanations on modelling methods and data sources are provided in this chapter for selected climate datasets.

Two key datasets have been used in HELiOS-Mining: the NCEP - CFSR climate reanalysis (National Centre for Climate Prediction Climate Forecast System Reanalysis) for wind speed (NCEP, 2010), and the Meteonorm dataset for solar data (Remund et al., 2004). Together, these datasets have been used to generate different climate scenarios and test RQ1 results under climatic extremes in an adequacy analysis. Details on data selection is given as follow.

6.1.1 *Solar data*

The Meteonorm dataset (Remund et al., 2004) is the main source of solar data for this research. The direct normal irradiance (DNI) and total tilted irradiance have been extracted for each selected mine. This dataset relies on both satellite observations and ground station measurements to generate hourly data for any geographical coordinate. Specifically, the ground station measurement data of Meteonorm are based on various datasets such as Swissmet of MeteoSwiss (1986-2005), Globalsod (2000-2009), GEBA Global Energy Balance Archive (1986-2005), and NREL (1961-1990). Both ground station measurements and satellite data were combined for locations where the nearest meteorological station is located 30-200 km away. Alternatively, the solar data of locations situated further than 200 km away from radiation measurements are solely based on satellite data. The Meteonorm interpolation method for processing satellite images is given in Rigollier et al. (2004).

A key output of Meteonorm is the ability to export hourly solar data for a typical year of solar inputs - based on stochastic simulations using Markov transition matrices and Kolmogorov-Smirnov (KS) validation test (Aguiar et al., 1988). This "typical year" provides the daily and seasonal patterns that are necessary for system design and sizing. These data were validated against in situ measurements or compared against other datasets in the data analysis phase of the PhD. Specifically, the in-situ dataset of the Universida Tecnica Federico Santa Maria was used for comparing hourly direct and indirect radiations in Calama, Chile (Romero, 2008) while the Meteonorm datasets of the Australian and Canadian mines were compared against the daily means of the NASA-SSE dataset at the same geographical coordinates (Stackhouse and Whitlock, 2008).

An additional feature of Meteonorm is the ability to export 10 years of hourly data. This extended dataset is one of the main data source for the adequacy analysis so as to identify the year with the lowest solar radiation in each mine, in terms of intensity and intermittency patterns. This worst case scenario (WCS) dataset is subsequently used as an input to HELiOS-Mining to measure the impact of lower resources on the energy index of reliability (EIR). Because the 10 year data extraction of Meteonorm is currently in a beta stage and is not corrected to long term averages, the selection of the year with the lowest solar radiation was subsequently validated against the NASA-SSE dataset with respect to the "no-sun" metric (Stackhouse and Whitlock, 2008) . This metric was particularly useful to determine the "worst case scenario" because it measures the minimum available insolation as % of average values over consecutive-day periods. The NASA-SSE and the Metenorm datasets have been therefore combined to select the solar inputs of the adequacy analysis. This selection was made by choosing the year of the Meteornom dataset where the minimum insolation over different time-periods is the nearest to the value of the NASA-SSE no-sun metric.

Table 6.1: North-Western Australia: Summary of solar data

Years	Sum of Global Horizontal (kWh/m2)	Minimum Available Insolation over 1 day (%)	Minimum Available Insolation over 3 days (%)	Minimum Available Insolation over 7 days (%)	Average Minimum Available Insolation over 1/3/7 days (%)
1	2192	16%	34%	59%	36%
2	2153	29%	39%	61%	43%
Wost Yr	2186	10%	27%	42%	26%
4	2212	24%	59%	66%	50%
5	2160	20%	41%	66%	42%
6	2223	27%	48%	76%	50%
7	2236	24%	59%	77%	54%
Best Yr	2255	37%	52%	78%	56%
9	2233	10%	40%	68%	39%
10	2158	21%	51%	66%	46%
Reference Yr	2205	27%	52%	74%	51%
NASA-SSE (22 years of data)	2212	10%	21%	43%	25%

An example of the solar data selection is provided in table 6.1 where the "Worst Yr" is the worst case scenario (WCS) of the adequacy analysis and the "Reference Yr" is the selected year for the base cases of the previous chapter. Appendix B on page 295 provides additional data tables and plots that compare the reference years against the 10 year dataset in all selected mining regions.

6.1.2 *Wind data*

Whereas the Meteonorm dataset is specifically designed for sizing solar systems, the wind speed dataset given by Meteonorm is only providing approximate wind speed data and is not intended for designing wind power plants (Remund et al., 2004). The NCEP-CFSR climate reanalysis dataset was instead used for wind data in HELiOS-Mining.

Sharp et al. (2015) have shown that this dataset is relatively well correlated with in situ measurements of both onshore and offshore wind speeds. This dataset covers the period from 1980 and 2010 at a resolution of approximately 38 km². This dataset has been validated by two different approaches depending on the mining region.

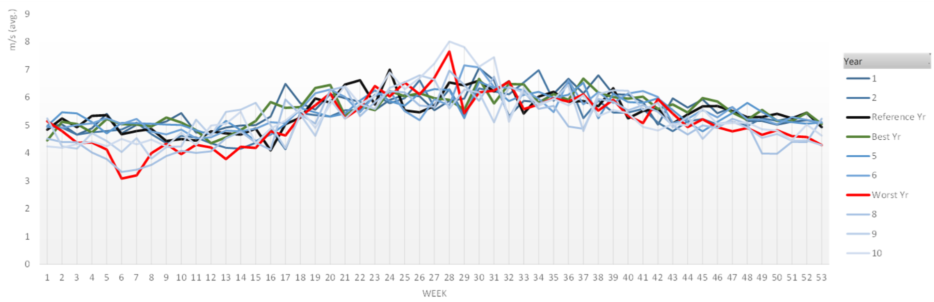
ATACAMA, CHILE; NORTH-WESTERN AUSTRALIA: Ten years of wind data have been extracted from the CFSR dataset for all mines. In this dataset, the worst case scenario for wind speed was identified based on the minimum number of hours for which the wind speed is above five meters per second for 1, 3, and 7 consecutive days - referred as "no-wind" in this study. The reference year represents the year for which the no-wind metric is the nearest to the 10 years average.

Table 6.2: Atacama, Chile: Summary of wind data

Years	Mean Wind Speed (m/s)	Nb of hours above 5 m/s	Minimum nb of hours above 5 m/s over 1 day	Minimum nb of hours above 5 m/s over 3 days	Minimum nb of hours above 5 m/s over 7 days
1	5.58	4497	6	22	56
2	5.30	4205	6	20	48
Reference Yr	5.48	4324	0	18	47
Best Yr	5.59	4531	6	21	57
5	5.48	4341	5	21	51
6	5.53	4339	4	21	52
Worst Yr	5.16	4264	0	2	11
8	5.05	4158	0	0	23
9	5.27	4561	2	17	48
10	5.40	4526	0	17	48
Average	5.38	4375	3	14	39

Table 6.2 and figure 6.1 illustrate the averages wind speed and no-wind metrics for the Atacama region - see appendix B on page 295 for further data tables and plots on wind data selection. The reference year is the basis of the cost optimisation of the previous chapter whereas the worst case scenario is selected in this adequacy analysis.

Figure 6.1: Atacama, Chile: Weekly average wind speed over 10 years



YUKON, CANADA: Past analyses suggest that CFSR presents the worst correlation coefficients with in situ measurements for sites located at high elevations (Sharp et al., 2015). Because the Yukon mine is located in a mountainous area and far away from meteorological stations (between 270 and 600km away), the extrapolated data from CFSR lack precision. Specifically, it was found that the CFSR outputs for this site were widely different than in situ measurements (Pinard, 2007) and mesoscale analyses (Environment-Canada, 2003).

As a result, the wind data of the Canadian mine are adjusted against another dataset in order to improve accuracy. The wind dataset of the Canadian Meteorological Centre (CMC) was selected to complement the CFSR dataset. This dataset is based on a mesoscale analysis which takes into consideration altitude and surface roughness of the entire Canadian territory (Environment-Canada, 2003). These data have been used to linearly scale the CFSR data to the seasonal means of the CMC dataset at the same geographical coordinate. Finally, a similar selection process than other mines was applied to select the worst case scenario and the reference year among the 10 year dataset. Table 6.3 shows the different wind speed values for this selection.

Table 6.3: Yukon, Canada: Summary of wind data

Years	Mean Wind Speed (m/s)	Nb of hours above 5 m/s	Minimum nb of hours above 5 m/s over 1 day	Minimum nb of hours above 5 m/s over 3 days	Minimum nb of hours above 5 m/s over 7 days
1	9.98	6809	0	2	25
Best Yr	10.12	6902	0	5	31
3	9.37	6823	0	3	38
4	9.54	6927	0	0	36
Reference Yr	8.59	6386	0	0	18
6	9.65	6888	0	2	29
Worst Yr	7.18	5414	0	0	6
8	7.10	5412	0	0	12
9	7.13	5706	0	0	7
10	7.15	5933	0	0	9
Average	8.58	6320	0	1	21

6.2 VALUE OF FOREGONE PRODUCTION

The value of foregone production (VFP) is the valuation of the potential economic losses associated with power shortages (Billinton et al., 1996) - see methodology in section 3.7.3. The VFP is calculated for the three mining regions of this thesis with respect to annual power demand and annual revenue. Table 6.4 provides the results of this calculation. It was found that the VFP is situated between \$0.86 and \$3.06/kWh in selected mines. The grade of the copper ore was found to be directly associated with the VFP values. Accordingly, the power demand is significantly higher in mines with lower ore grades as more energy is required to extract the mineral from the ore. This outcome means that one unit of energy has a different reliability worth depending on mineralisation grades.

Table 6.4: Value of Foregone Production for each mine

	Spence (Chile)	Casino (Canada)	Sandfire (Australia)
Annual Revenue (R)	$M 940	$M 773	$M 377
Annual Power Demand (E)	468 GWh	895 GWh	123 GWh
VFP (R/E)	**$2/kWh**	**$0.86/kWh**	**$3.06/kWh**
Copper Ore Grade (average measured resources)	**0.89%TCu (open-pit; supergene sulphide currently being exploited)**	**0.39%TCu (open-pit; supergene sulphide)**	**5%TCu (underground sulphide ore)**

Additional elements could be considered in the value of the foregone production such as: duration of shortages, equipment damages, and impact on profit. The duration of shortages is neglected in this research as it is assumed that each unit of energy is worth the same amount of revenue independently of time considerations. The equipment damage associated with power shortage was assessed to be minimal or insignificant by mining experts (Engelhard, 2016). Finally, a non-linear VFP value was initially considered for this study in order to account for decreasing reliability costs over time (as given in Balducci et al., 2002). Yet, given the results of the sensitivity analysis on VFP values in 6.4.1 on page 176, it was demonstrated that the consideration of higher VFP values (as a function of time) would not provide any additional insights.

6.3 ADEQUACY ANALYSES

Both the value of foregone production and the worst case scenario (WCS) climate data are combined in this analysis in order to characterise the impact of lower intermittent resources on reliability and system costs. This adequacy analysis is performed in two distinct steps. First, the LCOE of the RQ1 optimal hybrid power systems from section 5.1 on page 114 are recalculated with the WCS data and the VFP of each mine. Second, these power mixes are re-optimised by taking into consideration the value of lost load (VoLL), which is the annual total cost of all power shortages calculated by combining the LOEE and VFP metrics (see section 3.7.3). In other words, the optimisation algorithm of HELiOS-Mining aims to optimise the trade-off between reliability cost (i.e. VoLL) and reliability benefit (i.e. reduced capacity costs). Results are presented as follow for each off-grid mine.

6.3.1 *Atacama, Chile (Off-Grid)*

The results of the adequacy analysis for the Chilean mine are presented in table 6.5 on the following page. The table is structured with three different parts that provide results on each hybrid renewable power system. The first part (RQ1) gives the results that were found in the previous chapter in relation to the share of renewable power, share of fuel-based power, and LCOE. The second part (Non-Optimised Adequacy Analysis) is an analysis of the direct impact of both WCS climate data and VFP on the outputs of RQ1 with respect to reliability, generation shares, and LCOE. The third part (Optimised Adequacy Analysis) compares the results of the RQ1 against a set of new optimisation runs in which the model is allowed to change the size of each power plant in order to optimise the LCOE (while accounting for the value of foregone production). Key insights on these results are provided as follow.

Table 6.5: Results of the adequacy analysis: Atacama, Chile (Off-Grid)

Scenarios		Results RQ1			Non-Optimised Adequacy Analyis						Optimised Adequacy Analyis					
#	System	Renewable Share	Diesel & Gas-backup Share	LCOE (US$/kWh)	Rank	EIR	Change of Renewable Share (Abs.)	Change of Diesel/Gas-Backup Share (abs.)	VoLL (M$/Yr)	LCOE (US$/kWh)	Rank	EIR	Change of Renewable Share (Abs.)	Change of Diesel/Gas-Backup Share (abs.)	VoLL (M$/Yr)	LCOE (US$/kWh)
1	Wind & PV & CSP Tower (Gas backup) & Diesel	80%	20%	0.167	1	100.00%	-2%	2%	0.0	0.171	1	99.98%	-6%	6%	0.15	0.169
2	Wind & PV & CSP Tower & Diesel	83%	17%	0.185	3	100.00%	-3%	3%	0.0	0.193	3	99.99%	-4%	4%	0.12	0.192
3	Wind & PV & CSP Tower (Gas backup)	79%	21%	0.185	2	99.96%	-2%	2%	0.4	0.189	2	99.69%	-2%	2%	2.90	0.184
4	CSP Tower & Diesel	83%	17%	0.192	4	100.00%	-2%	2%	0.0	0.198	4	100.00%	-7%	7%	0.01	0.196
5	CSP Parabolic Trough (Gas backup) & Diesel	62%	38%	0.210	5	100.00%	0%	0%	0.0	0.210	5	99.98%	-5%	5%	0.19	0.207
6	Wind & PV & CSP Parabolic Trough & Diesel	73%	27%	0.220	6	100.00%	-2%	2%	0.0	0.225	6	99.99%	-4%	4%	0.11	0.224
7	PV & CSP Parabolic Trough & Diesel	71%	29%	0.223	7	100.00%	-2%	2%	0.0	0.228	7	99.99%	-3%	3%	0.13	0.227
8	Wind & PV & Battery & Diesel	49%	51%	0.229	9	100.00%	-2%	2%	0.0	0.235	8	99.99%	-6%	6%	0.12	0.233
9	Wind & PV & Diesel	41%	59%	0.232	8	100.00%	-1%	1%	0.0	0.234	9	99.99%	-2%	2%	0.12	0.233
10	PV & Diesel	32%	68%	0.236	11	100.00%	-1%	1%	0.0	0.239	12	100.00%	-1%	1%	0.01	0.239
11	CSP Parabolic Trough & Diesel	71%	29%	0.236	10	100.00%	0%	0%	0.0	0.236	10	100.00%	-1%	1%	0.00	0.238
12	PV Tracking & Diesel	32%	68%	0.237	12	100.00%	-1%	1%	0.0	0.239	13	100.00%	-1%	1%	0.01	0.239
13	PV & Battery & Diesel	52%	48%	0.238	13	100.00%	-2%	2%	0.0	0.243	11	100.00%	-19%	19%	0.01	0.238
14	Wind & Diesel	32%	68%	0.240	14	100.00%	-5%	5%	0.0	0.252	14	99.98%	-2%	2%	0.16	0.252
15	Diesel only	0%	100%	0.283	15	100.00%	0%	0%	0.0	0.283	15	99.98%	0%	0%	0.17	0.284
16	Wind & PV & Battery	100%	0%	0.358	16	98.30%	0%	0%	15.5	0.399	16	98.25%	0%	0%	16.35	0.362
17	PV & Battery	100%	0%	0.382	17	96.90%	0%	0%	28.9	0.470	17	96.02%	0%	0%	37.21	0.452
18	Wind & Battery	100%	0%	0.404	18	93.10%	0%	0%	64.4	0.605	18	95.85%	0%	0%	38.81	0.552
	Average	63.2%	36.8%			99.3%	-1.4%	1.4%				99.4%	-3.5%	3.5%		

NON-OPTIMISED ADEQUACY ANALYSIS: Two main categories of results can be distinguished in the result table. First, the power systems that include fuel-based power have little or no change in reliability values (EIR) because they incorporate enough contingency reserve to compensate for lower levels of intermittent resources. Accordingly, the capacity factors of fuel-based alternatives are increasing in order to meet demand and minimise the value of foregone production. Second, power systems with no fuel-based power backup feature a significant reduction of EIR and an increase of LCOE. Interestingly, the scenario 16 that includes wind, solar, and battery is better able to cope with lower renewable resources than scenarios 17 and 18 that only include one type of intermittent resource. This outcome suggests that a combination of resources with different daily and seasonal patterns is directly associated with higher reliability levels and lower reliability costs - as previously demonstrated in section 5.2.1.1 on page 116.

OPTIMISED ADEQUACY ANALYSIS: A new iteration of the optimisation runs was performed in this analysis. Three major insights can be observed in the result table. First, fuel-based backup generation plants that feature low capacity factors and high unit costs have been maintained in the mix - i.e. fuel capacities have not been discarded. This outcome means that the value of foregone production is higher than the unit cost of fuel-based backup plants (see figure 6.5 on page 180 for additional details on unit costs). As a result, the optimal levels of reliability are close to the 100% mark and the value of lost load is minimal. Second, the fuel-based capacity has increased in some scenarios due to lower reserve capacity and higher capacity factors - resulting from lower levels of intermittent resources. Interestingly, in scenario 13 (PV & Battery & Diesel), there is a large decrease of storage capacity in the mix due to reduced levels of non-dispatchable resources. This result stresses that the LCOE of battery storage is more sensitive to input changes than other generation technologies, i.e. near break-even point. Finally, scenarios 16 to 18 are the only outcomes in which the optimal LCOE is associated with relatively low reliability values. This outcome is due to the increasingly high unit costs of battery storage for lower capacity factors. In these systems, it is more beneficial to forego a fraction of the mine's production rather than to increase storage capacities.

6.3.2 *Yukon, Canada (Off-Grid)*

The results of the adequacy analysis of the Yukon mine shown in table 6.6 on page 173 present different characteristics than other mines, due to lower solar resources and larger shares of fuel-based power. Specifically, RQ1 results include between 50% and 100% of fuel-based power whereas the optimal solution incorporates 100% of fuel-based power. The reliability index of the non-optimised adequacy analysis remains subsequently unchanged by lower renewable resources as there is enough fuel-based reserve capacity to cope with lower amount of intermittent resources. However, the LCOE of power systems that include renewable resources is negatively impacted. For instance, the LCOE of scenarios 2 and 3 (CCGT, diesel, and wind power) increase by 2 to 5% whereas the share of wind power is reduced by 2 to 6% respectively.

In the optimised adequacy analysis, the convergence between reliability costs and optimal capacity levels is reached in the nearby area of 99.9% of reliability. At this level, the value of lost load is minimal and the capacity factors of generation plants are optimised. Note that the wind resources in scenario 2 and 3 are fully discarded by the optimisation algorithm due to their near-optimal characteristics.

Table 6.6: Results of the adequacy analysis: Yukon, Canada (Off-Grid)

Scenarios		Results RQ1			Non-Optimised Adequacy Analyis						Optimised Adequacy Analyis					
#	System	Renewable Share	Diesel & GT/CCGT Share	LCOE (US$/kWh)	Rank	EIR	Change of Renewable Share (Abs.)	Change of Diesel/GT/CCGT Share (abs.)	VoLL (M$/Yr)	LCOE (US$/kWh)	Rank	EIR	Change of Renewable Share (Abs.)	Change of Diesel/GT/CCGT Share (abs.)	VoLL (M$/Yr)	LCOE (US$/kWh)
1	CCGT & Diesel	0%	100%	0.150	1	100.00%	0%	0%	0.00	0.150	1	99.94%	0%	0%	0.49	0.148
2	Wind & CCGT & Diesel (Near-Optimal 1)	8%	92%	0.151	2	100.00%	-2%	2%	0.00	0.153	2	99.94%	-8%	8%	0.49	0.148
3	Wind & CCGT & Diesel (Near-Optimal 2)	25%	75%	0.155	3	100.00%	-6%	6%	0.00	0.162	3	99.94%	-25%	25%	0.49	0.148
4	GT & Diesel	0%	100%	0.157	4	100.00%	0%	0%	0.00	0.157	4	100.00%	0%	0%	0.00	0.157
5	Wind & PV & Diesel	48%	52%	0.256	5	100.00%	-8%	8%	0.01	0.280	5	99.98%	-7%	7%	0.19	0.279
6	Wind & PV & CSP Tower & Diesel	50%	50%	0.256	6	100.00%	-8%	8%	0.00	0.281	6	99.97%	-8%	8%	0.26	0.279
7	Wind & CSP Tower & Diesel	54%	46%	0.259	7	100.00%	-9%	9%	0.00	0.286	7	99.97%	-10%	10%	0.20	0.285
8	Wind & Diesel	38%	62%	0.262	8	100.00%	-8%	8%	0.00	0.288	8	99.98%	-9%	9%	0.14	0.287
9	PV & Diesel	18%	82%	0.309	9	100.00%	0%	0%	0.00	0.310	9	99.98%	0%	0%	0.19	0.309
10	PV Tracking & Diesel	18%	82%	0.309	10	100.00%	0%	0%	0.00	0.310	10	99.98%	-1%	1%	0.19	0.309
11	PV & CSP Tower & Diesel	18%	82%	0.309	11	100.00%	0%	0%	0.00	0.310	11	99.98%	0%	0%	0.18	0.309
12	CSP Tower & Diesel	32%	68%	0.316	12	100.00%	-1%	1%	0.00	0.320	12	99.97%	-3%	3%	0.20	0.320
13	Diesel only	0%	100%	0.325	13	100.00%	0%	0%	0.00	0.325	13	99.97%	0%	0%	0.21	0.324
	Average	23.8%	76.2%			100.0%	-3.3%	3.3%				100.0%	-5.4%	5.4%		

6.3.3 *North-Western Australia (Off-Grid)*

The adequacy analysis of the off-grid Australian mine presents similar characteristics to the off-grid Chilean mine. Yet, a few additional observations are given in result table 6.7 on the facing page.

In scenario 2 of the optimised adequacy analysis, the EIR is below the 100% mark whereas all other scenarios that include fuel-based power reach their optimal LCOE at 100% of reliability. This result is directly associated with the type of fuel-based backup power of this scenario. Because there is no diesel backup, the gas-backup of the CSP plant is the only generation alternative at times of low intermittency and low storage reserves. The CSP plant is modelled with two steam turbines that feature an availability rate of 96% (Jorgenson et al., 2013), which implies that there are times at which the capacity of the CSP plant is reduced by half. As a result, it is necessary to largely oversize the CSP power block in order to reach 100% of reliability. On the contrary, the scenarios with diesel backup plant are modelled on a modular basis with multiple diesel generators - which significantly reduces the outage rates of the diesel plant. As a result, the optimal level or reliability converges at 99.91% in this scenario.

Table 6.7: Results of the adequacy analysis: North-Western Australia (Off-Grid)

Scenarios		Results RQ1			Non-Optimised Adequacy Analyis						Optimised Adequacy Analyis					
#	System	Renewable Share	Diesel & Gas-backup Share	LCOE (US$/kWh)	Rank	EIR	Change of Renewable Share (Abs.)	Change of Diesel/Gas-Backup Share (abs.)	VoLL (M$/Yr)	LCOE (US$/kWh)	Rank	EIR	Change of Renewable Share (Abs.)	Change of Diesel/Gas-Backup Share (abs.)	VoLL (M$/Yr)	LCOE (US$/kWh)
1	CSP Tower (Gas backup) & Diesel	75%	25%	0.185	1	100.00%	-2%	2%	0.0	0.188	1	100.00%	-3%	3%	0.0	0.187
2	Wind & PV & CSP Tower (Gas backup)	68%	32%	0.206	2	99.91%	-1%	1%	0.4	0.211	2	99.91%	8%	-8%	0.4	0.205
3	Wind & PV & CSP Tower & Diesel	84%	16%	0.208	3	100.00%	-2%	2%	0.0	0.215	3	100.00%	-3%	3%	0.0	0.214
4	PV & CSP Tower & Diesel	85%	15%	0.209	4	100.00%	-3%	3%	0.0	0.216	4	100.00%	-4%	4%	0.1	0.215
5	Wind & PV Tracking & CSP Tower & Diesel	84%	16%	0.209	5	100.00%	-2%	2%	0.0	0.216	5	100.00%	-2%	2%	0.0	0.216
6	Wind & CSP Tower & Diesel	85%	15%	0.209	6	100.00%	-3%	3%	0.0	0.217	6	100.00%	-6%	6%	0.0	0.216
7	CSP Tower & Diesel	86%	14%	0.210	7	100.00%	-3%	3%	0.0	0.218	7	100.00%	-7%	7%	0.0	0.217
8	Wind & PV & CSP Parabolic Trough & Diesel	62%	38%	0.244	8	100.00%	-1%	1%	0.0	0.246	8	100.00%	0%	0%	0.0	0.246
9	Wind & PV & Battery & Diesel	55%	45%	0.249	9	100.00%	-1%	1%	0.0	0.250	10	100.00%	-1%	1%	0.0	0.250
10	Wind & PV & Diesel	52%	48%	0.251	10	100.00%	0%	0%	0.0	0.252	9	100.00%	-5%	5%	0.0	0.249
11	PV & CSP Parabolic Trough & Diesel	66%	34%	0.255	11	100.00%	-1%	1%	0.0	0.259	11	100.00%	-3%	3%	0.0	0.256
12	PV & Battery & Diesel	52%	48%	0.264	14	100.00%	-1%	1%	0.0	0.268	14	100.00%	-20%	20%	0.0	0.262
13	PV & Diesel	32%	68%	0.260	12	100.00%	-1%	1%	0.0	0.262	12	100.00%	-1%	1%	0.0	0.262
14	PV Tracking & Diesel	32%	68%	0.262	13	100.00%	0%	0%	0.0	0.263	13	100.00%	2%	-2%	0.0	0.262
15	Wind & Diesel	39%	61%	0.265	15	100.00%	-1%	1%	0.0	0.268	15	100.00%	-1%	1%	0.1	0.268
16	CSP Parabolic Trough & Diesel	75%	25%	0.265	16	100.00%	-1%	1%	0.0	0.269	16	100.00%	-3%	3%	0.0	0.269
17	Diesel only	0%	100%	0.310	17	100.00%	0%	0%	0.0	0.310	17	100.00%	0%	0%	0.0	0.310
18	Wind & PV & Battery	100%	0%	0.381	18	96.80%	0%	0%	11.9	0.516	18	97.30%	0%	0%	10.0	0.502
19	PV & Battery	100%	0%	0.490	19	96.80%	0%	0%	12.0	0.624	19	96.40%	0%	0%	13.4	0.526
	Average	64.9%	35.1%			99.7%	-1.2%	1.2%				99.7%	-2.5%	2.5%		

6.4 SENSITIVITY ANALYSIS

Previous analyses have shown that there is no or little economic value to lower the reliability of hybrid power systems that include fuel-based backup capacities. Fuel-based backup plants were systematically maintained in the mix while accounting for the VFP values of each mine. This result suggests that the unit cost of fuel-based backup power is lower than the VFP. In this section, this hypothesis is tested by considering different VFP values as well as constraining the EIR to lower levels.

These sensitivity analyses have been performed on the CSP and no-CSP base cases, which represent the least-cost power systems with and without CSP alternatives - as given in table 5.3 on page 125.

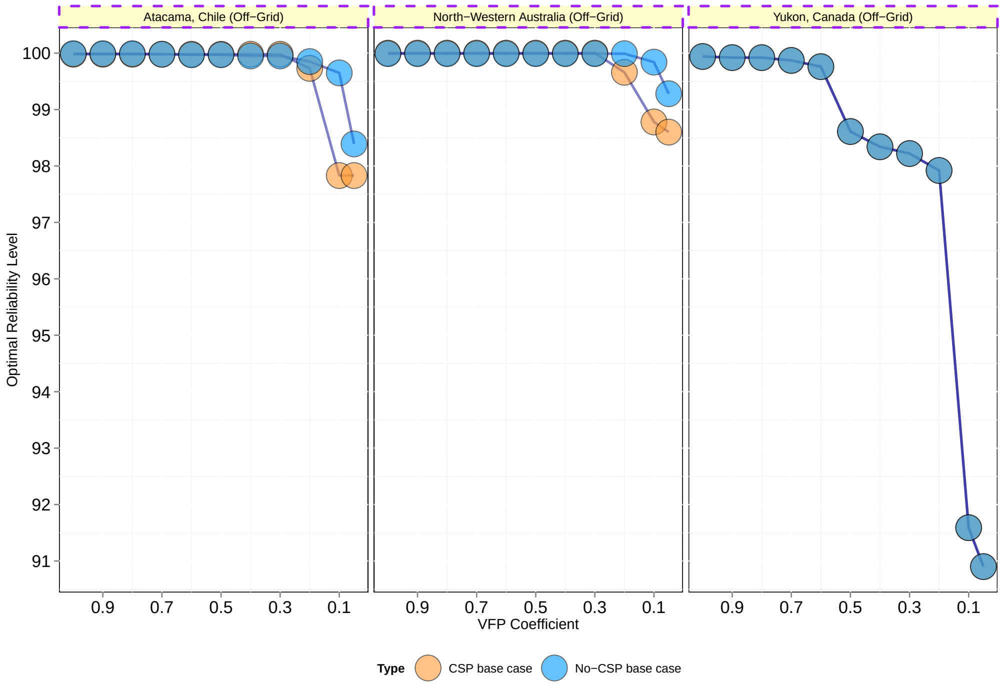
6.4.1 *Value of foregone production*

In this sensitivity analysis, the value of foregone production (VFP) is incrementally reduced in each optimisation run. The aim being to find the VFP level at which lower reliability values do provide economic benefits. Higher VFP levels have not been tested because section 6.3 on page 168 has conclusively demonstrated that initial VFP assumptions are already associated with near 100% reliability levels - hence higher VFP values could only validate these results as reliability levels above 100% are not possible.

Figure 6.2 on the next page presents the results of this analysis. Key observations are provided as follow.

- Reliability levels below 99% become economically viable for VFP values between $0.20-0.43 per kWh which represent between 10% and 50% of the initial VFP assumption.
- Reliability levels below 99% are associated with capacity reductions for power plants with low capacity factors and high unit costs (i.e. backup or peaking capacity).
- CSP base case is more sensitive to lower VFP values than the no-CSP base case due to the relatively low availability rate of CSP alternatives - hence requiring larger diesel backup capacities. Accordingly, there is a smaller room for reducing backup capacities as the VFP decreases.
- In the Canadian mine, the backup capacities (i.e. diesel plant with low capacity factor and high unit cost) of the CCGT plant are significantly reduced for lower

Figure 6.2: Optimal reliability level as a function of the value of foregone production



VFP values. The EIR is more sensitive to VFP changes than other mines because of the relatively low initial VFP value in this mine (due to the low ore grade).

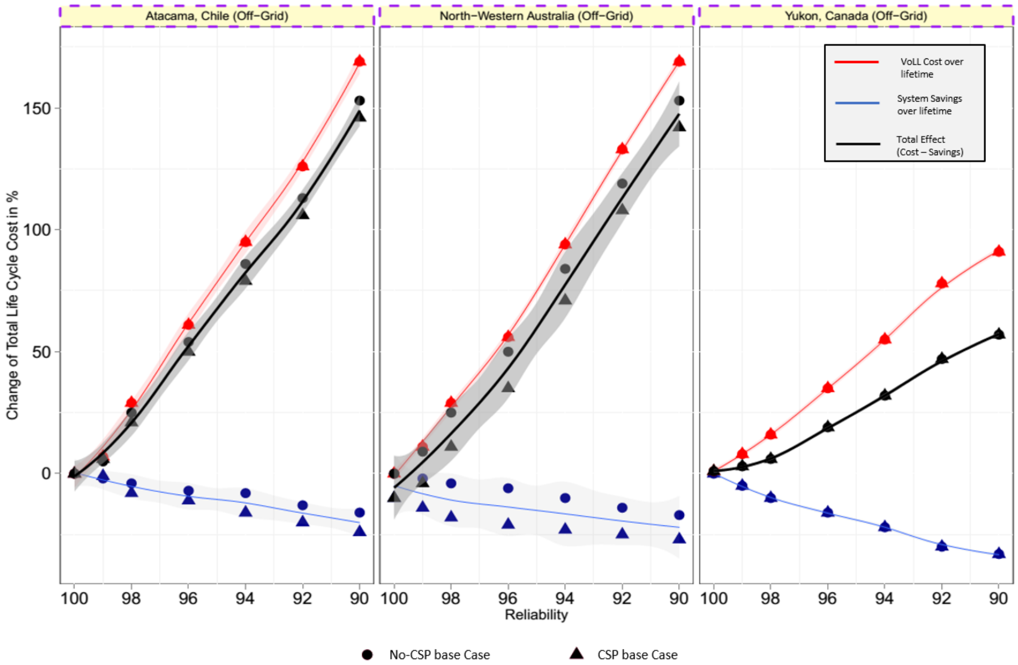
Overall, this analysis has conclusively demonstrated that reliability coefficients are relatively insensitive to changes in VFP. An important VFP reduction is required to economically justify lower reliability coefficients. It is expected that such low VFP values would require a significant decrease of either commodity prices or ore grade (-50 to 90%). Mines that would encounter these conditions might generate economic benefits by shutting down the production at times of low renewable resources. Further discussion points on commodity prices and geological uncertainty are provided in chapter 8 on page 213.

6.4.2 *Energy Index of Reliability*

In this analysis, an additional constraint is placed on the EIR value in HELiOS-Mining. The aim being to measure the outcome of lower EIR values on system costs and benefits.

Figure 6.3 on the next page presents the results of this analysis. It suggests that the total economic effect associated with EIR values below 100% is a net cost to the mine. In other words, the cost of reliability (VoLL) is always higher than the savings resulting

Figure 6.3: Comparison of Total Life Cycle Cost and Energy Index of Reliability



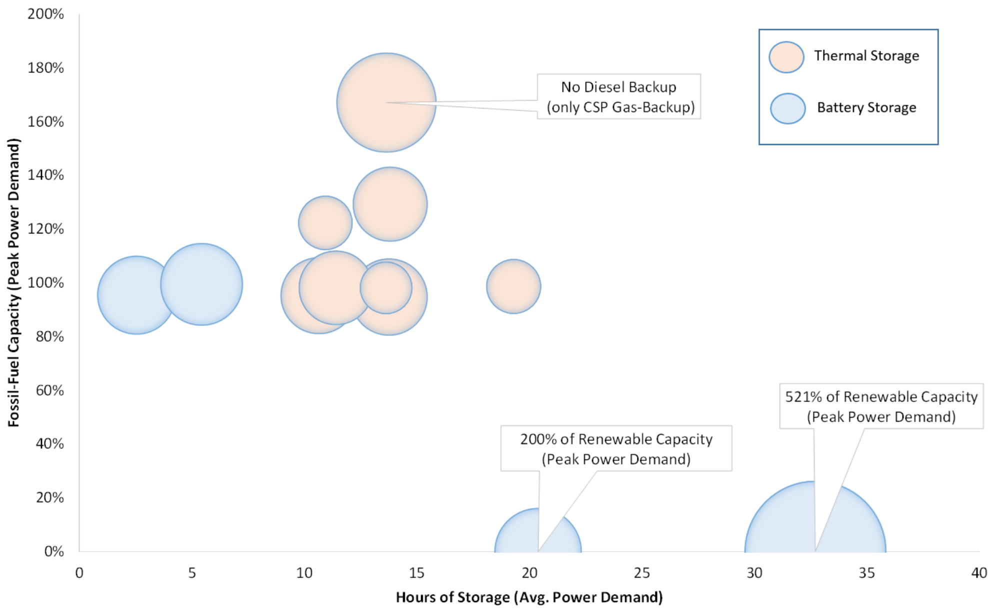
from lower reliability levels. This result is consistent with the previous analysis on VFP values.

Further, the cost savings associated with the CSP base case were found to be consistently larger than the no-CSP base case. This outcome is directly associated with the capacity factors of both CSP and no-CSP base cases. First, when diesel power is included in a CSP system, the capacity factor of the diesel plant tend to be low as it is infrequently used (i.e. backup only), which therefore implies that the unit cost is high and significant benefits can be generated by removing the diesel plants. Conversely, the diesel plants in no-CSP base cases are frequently used and removing such capacity generates higher costs of reliability.

6.5 SUMMARY

The impact of lower levels of intermittent resources was analysed in this chapter with respect to the value of lost load and the value of foregone production. Based on this analysis, a number of observations have been proposed. First, power systems that include fuel-based power feature little or no change in reliability values (EIR). This result is consistent with the results of previous chapter. Most of RQ1 power systems include enough fuel-based capacity to completely meet the peak power demand. As a consequence, the reliability of these power systems is relatively insensitive to variations in renewable resources. Figure 6.4 further illustrates this characteristic by comparing fuel-based capacity against storage capacity. It can be observed that most RQ1 scenarios include between 95% and 167% of fuel-based capacity. Power systems based on CSP alternatives have the largest backup capacities due to the relatively high outage rates of the CSP power block.

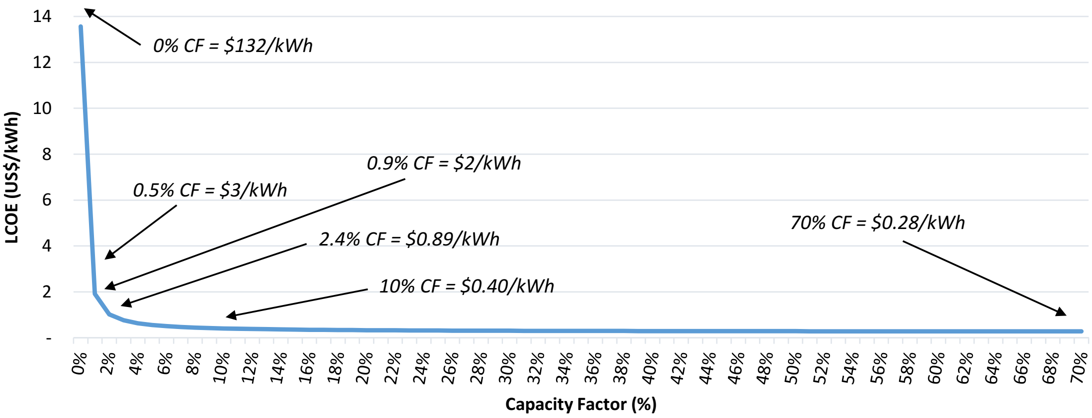
Figure 6.4: Fossil-fuel power capacity in RQ1 power mixes (Chile, Off-Grid)



Second, the optimal level of reliability for power systems with no fuel-based power was found to be significantly reduced when accounting for reliability costs. This outcome demonstrates that hybrid power systems with EIR values lower than 100% can be cost optimal only if no fuel-based resources are part of the system. Yet, such systems present much higher unit costs than hybrid power systems that do include fuel-based power in the mix.

Third, the optimised adequacy analysis has shown that fuel-based capacities provide an economical value to the generation mix, even at low capacity factors. This outcome suggests that the unit cost of fuel-based alternatives is lower than the value of foregone production. Figure 6.5 on the next page provides further evidence for this outcome. Specifically, it is shown that the unit cost of diesel power is significantly lower than the VFP of all mines for capacity factors higher than 2.4%. This further suggests that, based on the VFP assumptions of this research, it is economically beneficial to maintain diesel capacities in the generation mix, even for very low capacity factors. Interestingly, this outcome is fully consistent with the findings of Huneke et al. (2012) that focused on wind and diesel stand-alone generation.

Figure 6.5: Diesel power generation: LCOE and capacity factor



Finally, the sensitivity analyses on VFP and EIR have shown that RQ1 base cases are relatively insensitive to lower VFP values. Lower EIR values become economically viable for a VFP reduction comprised between 50 and 90%. The analysis on EIR values has subsequently validated this hypothesis. Specifically, the cost of reliability was found to be always superior to the cost savings for reliability levels below 100% (with respect to base cases).

While this analysis has focused on changing the amount of intermittent resources, an additional analysis on the changes in power demand could have been additionally performed. Yet, because the power demand of mining plants is characterised by little or no variations in daily and seasonal demand (as shown in section 3.9 on page 72), the impact of such demand analysis would not provide any valuable insight. Lower and higher levels of power demands would only mean that the power system should be linearly resized. On the contrary, a detailed analysis of demand patterns would provide valuable information in a domestic context or in industries with discontinuous processes.

7

PORTFOLIO THEORY: COST RISK

Previous results have conclusively demonstrated that the cost of CSP hybrid power systems is lower than other systems or near-optimal in three out of the four mines considered in this research. These results also have suggested that larger shares of renewable power are associated with large capital investments and relatively low variable costs. On average, the power mixes of the CSP base cases were found to feature over 65% higher capital costs than no-CSP alternatives. These different ratios of capital costs over lifecycle costs imply that different solutions have different capital risk profiles. Capital intensive alternatives are more sensitive to changes in mine-life values. Alternatively, fuel intensive alternatives are more sensitive to changes in fuel prices and fuel policies. The trade-offs between these different risks is investigated in this chapter. A portfolio framework is introduced in order to compare these different risk factors. A decision-analysis is subsequently proposed in order to rank the investment alternatives according to different risk perspectives. Accordingly, the research question addressed in this chapter is the following: What is the influence of cost risks on the economics of hybrid renewable power systems?

This chapter is structured as follows. First, the underlying assumptions of the portfolio framework are stated in section one. Second, the cost risk of various fuel types is characterised in relation to the historical times-series of fuel prices. In section three, the disaggregated cost risks are presented in a portfolio of different technological mixes with respect to several risk factors. The decision space is analysed and discussed in the last section of this chapter.

7.1 SCOPE OF PORTFOLIO THEORY

The aim of portfolio theory is to optimise both cost and cost risk, where the cost risk represents the strength and likelihood of potential cost variations over time. A number of different risk categories can be considered in such analysis.

The first cost category relates to fixed costs, which include capital costs, cost overruns, and fixed O&M costs. A key area of interest in this category relates to the investment period (i.e. mine-life) that is used to discount the annual investment costs (through a capital recovery factor). The mine-life is particularly interesting because it is associated with the risk of early market exit, which relates to various factors of uncertainty such as commodity price cycles as well as political, geological, and operational risks. Capital cost overruns are neglected in this analysis due to the relatively low complexity and maturity of in-scope technologies (i.e. wind, PV, diesel, battery). Yet, a contingency cost is considered in the cost structure of CSP plants, which is arguably the most complex power alternative of this research. Fixed O&M costs are also neglected from the portfolio analysis because they represent a negligible fraction of total life-cycle costs.

The second cost category relates to variable costs, which consider maintenance costs, fuel costs, and carbon costs. On the one hand, the risks associated with maintenance costs are often neglected in portfolio theory due to their relatively small influence on total life-cycle costs. On the other hand, fuel costs and carbon costs can have a large influence on the competitiveness of hybrid renewable power systems as they represent up to 93% of total life cycle costs (TLCC) - depending on the amount of fuel-based power in a power system and given no carbon taxation (see appendix A on page 263 for more details).

7.1.1 *Assumptions*

A number of assumptions have been taken in order to model portfolio cost risk. First, the different portfolios of technologies are based on the results of research question one (RQ1) given in table 5.1 on page 114 - and further detailed in appendix A on page 263. The optimised results of research question two (RQ2) have not been chosen for this chapter. RQ2 results assume the worst case scenario for climate resources throughout the lifetime of the investment. While this assumption is useful to perform an adequacy analysis, the "typical year" of climate data used in RQ1 is more realistic to value system costs over several years of energy generation.

Second, HELiOS-Mining does not consider the salvage value of generation plants. A salvage value of zero was not a limitation in previous research questions because the mine-life periods of selected mines are relatively similar to the lifetimes of selected power systems. This is, however, a limitation for the cost risk analysis of shorter mine-life periods. It is expected that this factor has a relatively limited impact because disposal and relocation costs should significantly offset the salvage value.

Third, the fuel costs are modelled using historical fuel prices that include both fuel and excise costs. As a result, the volatility of historical retail prices is used to measure the impact of fuel policies - using a probabilistic approach. Conversely, the cost risk assumption for carbon taxation is scenario-based because there is not enough historical data to generate meaningful time-series of carbon prices. Both fuel and carbon costs are used to model the LCOE for fuel costs only (without capital expenditure), which represents the fuel cost independently of the capacity factor.

Finally, the time-series of historical data have been corrected for inflation. The CPI of each country was applied to historical prices in order to derive real prices with a 2015 base year for both unit costs and cost risks - same unit than the LCOE of RQ1.

Additional methodological steps on portfolio modelling are given in section 3.8 on page 69.

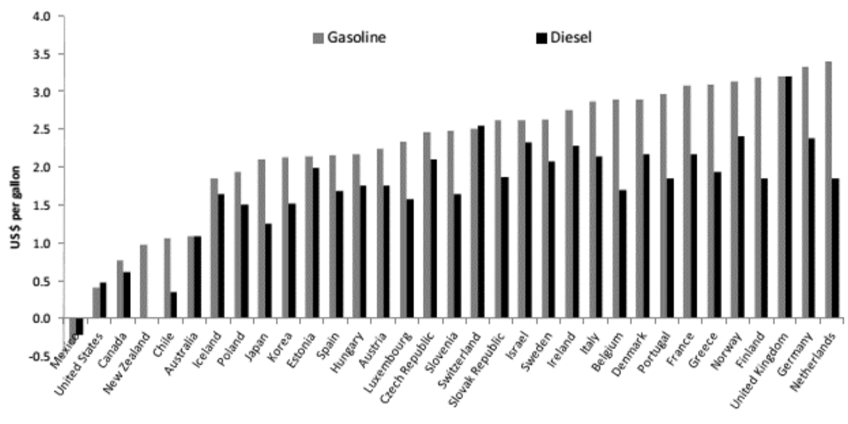
7.2 FUEL PRICES

Historical fuel prices serve as data inputs to characterise the volatility and the risk associated with future fuel price changes. Further details on the different steps leading to the cost risks are given as follow for selected fuels.

7.2.0.1 *Historical fuel prices*

While the historical data for fuel prices are considered on an after-tax basis, it is useful to highlight the weight of the excise tax in the selected countries of this research. Figure 7.1 provides this information for a number of OECD countries. Interestingly, the excise taxes in Canada, Chile, and Australia represent a relatively small fraction of fuel costs compared to other OECD countries. Hence it can be assumed that these countries experience a higher volatility in fuel prices than countries with higher excise rates.

Figure 7.1: Excise taxes on gasoline and diesel in OECD countries in year 2010 (Parry and Strand, 2012)



Source: OECD (2010), Figure 2.5.

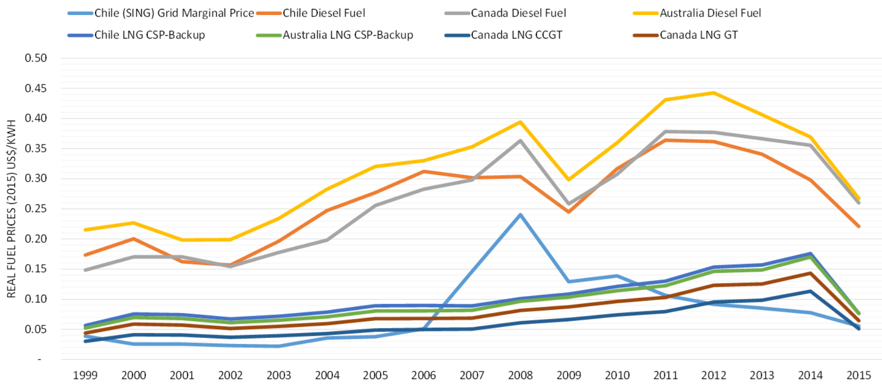
Figure 7.2 presents the mean real fuel prices for diesel, LNG, and grid prices, which are the relevant fuels associated with the results of RQ1 base cases (as given in table 5.3 on page 125). The average real fuel price change per year in Chile, Canada, and Australia is 2.9%, 4.9%, and 2.5% respectively for diesel fuel and 4.3%, 4.7%, and 5.6% for LNG prices[1].

Finally, the marginal generation costs of Chilean grid power have increased by an average of 13% over the period. Yet, the variation of retail grid prices is expected to be

[1] Historical real fuel prices have been modelled using CPI data and historical fuel prices (see section 4.6.5 on page 104 for data sources). Historical exchange rates for the conversion of local currency values to USD were obtained from Oanda (2016). Currency conversion of historical time-series was performed on a yearly-average basis.

relatively lower than the variation of marginal generation costs presented in this analysis - as transmission and distribution costs tend to be relatively independent of fuel market prices.

Figure 7.2: Historical variation of real fuel prices for selected mining regions



A key take-away from historical price data is that a real fuel price increase has been observed in the selected countries of this PhD. Because energy engineering analyses tend not to account for real price changes, the future generation costs of fuel-based alternatives might be higher than expected. The portfolio approach presented in this chapter provides a framework that considers both expected cost and changes in real fuel prices (i.e. fuel cost risk)[2].

7.2.1 *Time-series forecasting*

An autoregressive moving average (ARMA) approach was adopted to characterise the change in historical fuel prices and forecast fuel prices. A logarithmic transformation with a first order differencing was applied to historical data in order to achieve stationarity, which is a requirements of ARMA models (Aggarwal et al., 2009). This analysis was performed with the software @Risk in order to facilitate the data transformation process and select the best fitted ARMA model. Because many types of forecasting models are compared in @Risk, the final selection was based on the value of the fit ranking given by the Akaike's information criterion (AIC) as illustrated in figure 7.3. In this fit ranking, the AIC value compares the fit of ARMA processes (autoregressive, moving average), GBM (geometric Brownian motion) and its variations, and ARCH (autoregressive condi-

[2]Note that longer time-series could be used to model changes in historical prices. Because the retail diesel prices for Australia and Chile were not readily available before 1999, the scope of this analysis is constrained to the 1999-2015 time-period.

tional heteroscedasticity) and its variations. ARMA processes were found to provide a better fit for all price projections of this research.

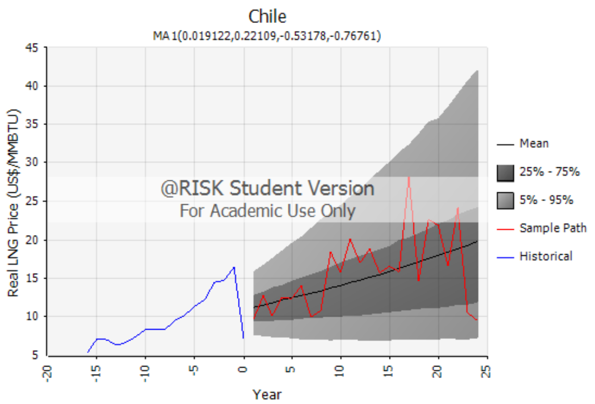
Figure 7.3: AIC fit ranking

Fit	AIC
MA(1)	-23.4553
AR(1)	-15.3046
ARCH(1)	-12.7521
MA(2)	-12.6302
ARMA(1,1)	-12.3101
AR(2)	-12.001
BMMR	-9.9216
GARCH(1,1)	-9.3056
GBM	N/A
GBMJD	N/A
BMMRJD	N/A

Other types of model could be considered for price forecasting such as general equilibrium analyses or artificial neural network (Li et al., 2005). The ARMA model was chosen because is it a parsimonious approach that provides insights on future price variances based on past variances. It is a relatively simple approach that does not aim at predicting future prices but rather at characterising the risk of price changes based on historical data - which is one objective of the portfolio approach.

The forecasting results of LNG prices are provided in figure 7.4. This figure provides the expected mean of future LNG prices as well as the uncertainty bands for each time period. The dark grey band represents the mean value +/- 25% while the light grey band represents two standard deviations from the mean. The output of this probabilistic analysis is an array formula that can be used to generate new time-series at each simulation run.

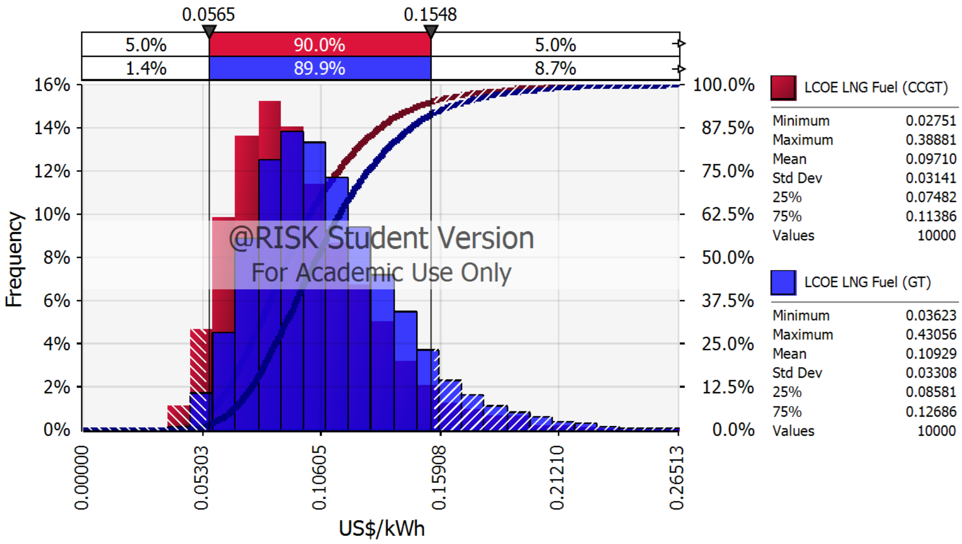
Figure 7.4: Uncertainty of future LNG prices



A Monte Carlo approach was subsequently applied to generate the standard deviation of fuel costs for several thousand simulations (until reaching convergence). The Monte Carlo simulation is using real prices as an input to HELiOS-Mining financial model. For each simulation run, the financial model discounts the future fuel costs in order to return the mean LCOE and levelised standard deviation over the investment period.

Figure 7.5 illustrates the result of this approach for both CCGT and gas turbine (GT) in the Canadian mine. Due to the higher efficiency of the combined cycle process, the mean LCOE and standard deviation of the CCGT plant are slightly lower than the GT plant. The cost risks of LNG prices are approximately \$0.031 and \$0.033/kWh with 50% of the

Figure 7.5: Monte Carlo analysis on future fuel prices for CCGT & GT (Canada)



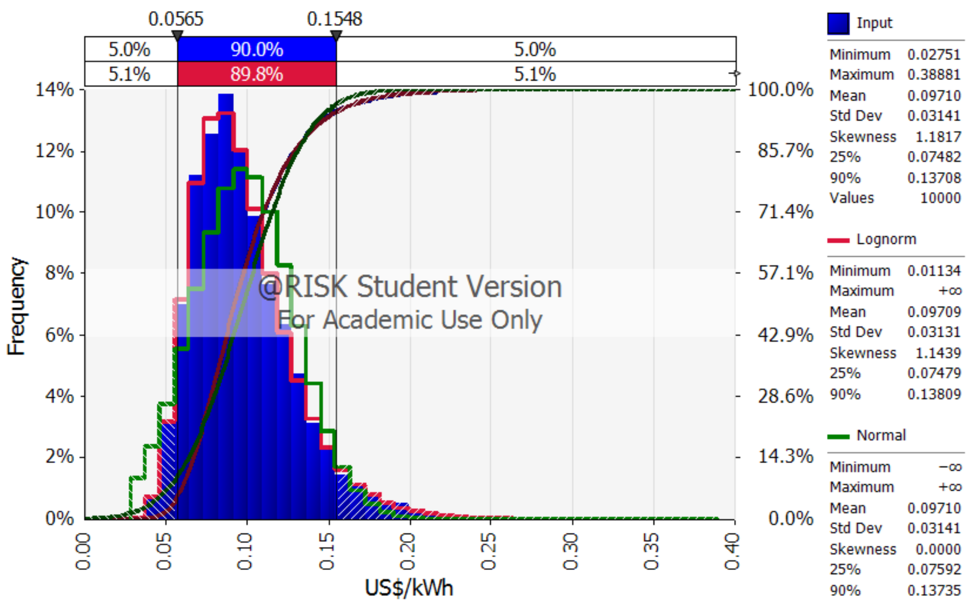
expected LCOE comprised between \$0.075 and \$0.114/kWh and \$0.086 and \$0.124/kWh for CCGT and GT respectively [3].

In this dataset, the best fit for the distribution of fuel costs is a lognormal distribution. Using a lognormal distribution on the CCGT time-series, the standard deviation shifts from \$0.03141 to \$0.03131/kWh, as presented on figure 7.6. Due to this relatively small change in standard deviation, the use of a normal distribution is expected to have a limited impact on portfolio results. A normal distribution is a requirement of the portfolio theory. The justification for this requirement is that return or cost can be approximated by a normal distribution. Extreme events, either positive or negative, are expected but their magnitude tend to have a limited impact over long time periods (Markowitz, 1952). In a similar line of argument, Jansen et al. (2006) states that the mean-variance theory is justified by the "Samuelson's 'Fundamental Approximation Theorem of Portfolio Analysis in Terms of Means, Variances, and higher Moments'. It proves *inter alia* that in many important circumstances the importance of all moments beyond the variance is much smaller than that of the expected value and variance. Disregarding moments higher than variance will generally not affect portfolio choice".

A similar approach was applied to other selected fuels. The time-series forecasting and Monte Carlo analyses for these fuels are provided in appendix C on page 301.

[3] All these forecast estimates have been levelised with a nominal discount rate of 12%.

Figure 7.6: Normal and lognormal CCGT cost distributions



7.2.2 *Correlation between fuel prices*

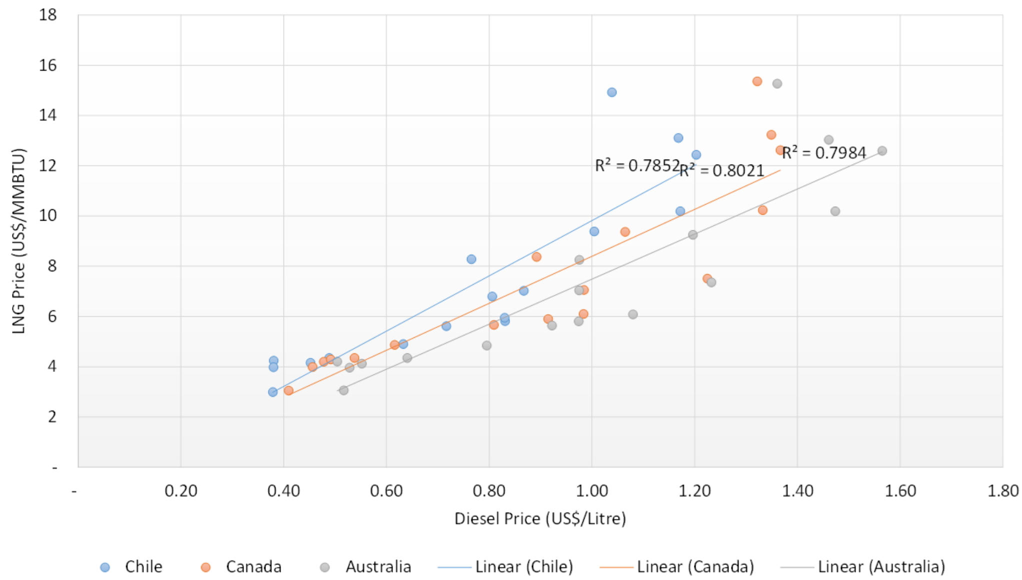
Whereas the portfolio approach focuses on the standard deviation of future fuel prices, it also accounts for the correlation between fuel prices. Specifically, a reduction of the cost risk is expected in portfolios with no perfect correlation between fuels. In other words, the exposure to an individual fuel cost risk can be reduced by diversifying the fuel sources in the portfolio. "If the returns on any two assets in the portfolio have a correlation of less than 1, the portfolio volatility will be less than the weighted average of the volatilities of the portfolio's individual assets" (Jansen et al., 2006).

In any given portfolio of the RQ1 results (given in table 5.1 on page 114), only two different fuels are ever selected together: LNG and diesel - whereas the fuel cost risk of renewable plants is considered to be zero. Figure 7.7 presents the R^2 correlation values for the three selected mining regions. Although the correlation scores are relatively high, no perfect correlation can be observed. It is therefore expected that the diversifying effect of the mean-variance theory will play a role if both fuels are combined in a given portfolio.

7.3 portfolio cost risk

In this section, the results of the portfolio theory are presented for various categories of risk. Cost risks associated with fuel prices are first presented along with the Pareto effi-

Figure 7.7: Correlation between fuel prices across mines

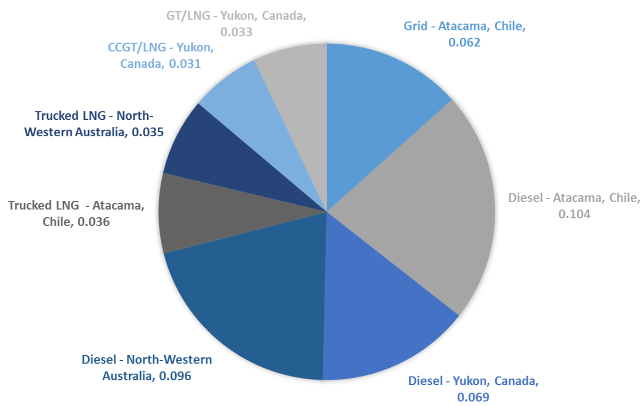


cient frontier. Although the mean-variance theory puts a great emphasis on fuel prices, other factors are of importance to characterise the broader cost risk of each portfolio. These other factors are presented in two subsequent subsections with respect to mine-life and carbon taxation cost risks. The total cost risk is then provided for each portfolio of generation technologies. All these risk factors are subsequently included in a decision-analysis framework in section 7.4 on page 197.

7.3.1 *Fuel Prices*

The levelised standard deviations of fuel costs for all selected fuels is presented in figure 7.8. These estimates represent the fuel cost risk before accounting for the correlation between fuel prices.

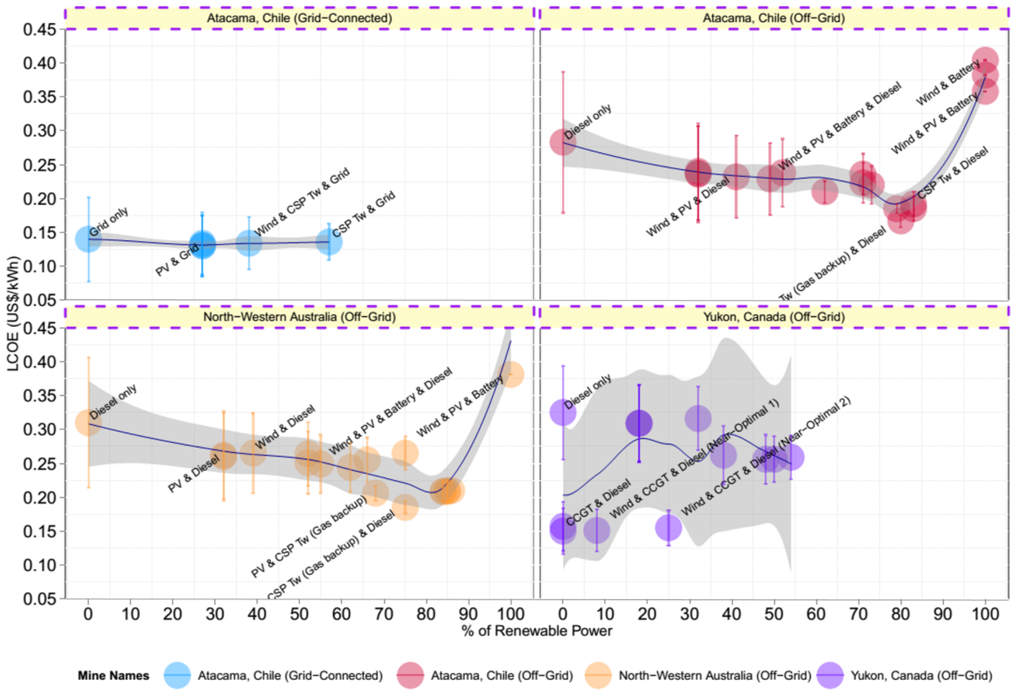
Figure 7.8: Levelised cost risks of selected fuels across three mining regions ($/kWh)



A number of insights can be derived from these results. First, diesel fuel presents the highest cost risk coefficients with approximately $0.10/kWh in the Australian and

Chilean mines and \$0.07 /kWh in the Yukon mine. This latter mine has a relatively lower cost risk due to a lower volatility in historical diesel prices. Together, the diesel cost risks account for approximately 60% of the selected fuel cost risks in this study. The cost risk associated LNG fuel varies between \$0.031 and \$0.036/kWh across mines [4]. Finally, the cost risk of grid power is relatively high with \$0.062/kWh due to the high historical volatility of grid prices in Northern Chile. A recent study identified that lower rainfall, drought, natural gas shortages, and earthquakes are accountable for the high volatility of Chilean grid prices (Grageda et al., 2016).

Figure 7.9: Upside and downside fuel cost risks



The fuel cost risk features two distinct sides. The upside cost risk represents the potential for lower costs than the expected mean while the downside cost risk refers to higher fuel costs. Figure 7.9 presents the optimal portfolios from RQ1 analyses with error bars that represent the upside and downside cost risks - results includes correlation effects between fuel prices. On the one hand, diesel-intensive portfolios feature the highest uncertainty while both downside and upside cost risks are decreasing with higher levels of renewable penetration. On the other hand, portfolios with large shares of LNG (e.g. CCGT alternative in Yukon) present significantly lower cost risks than their diesel counterparts.

[4]Note that this volatility only refers to the fuel component of LNG prices and does not consider transportation costs. As a result, the LNG cost risk is relatively similar for both trucked and pipeline LNG.

Figure 7.10: Fuel cost risk of generation portfolios across selected mines

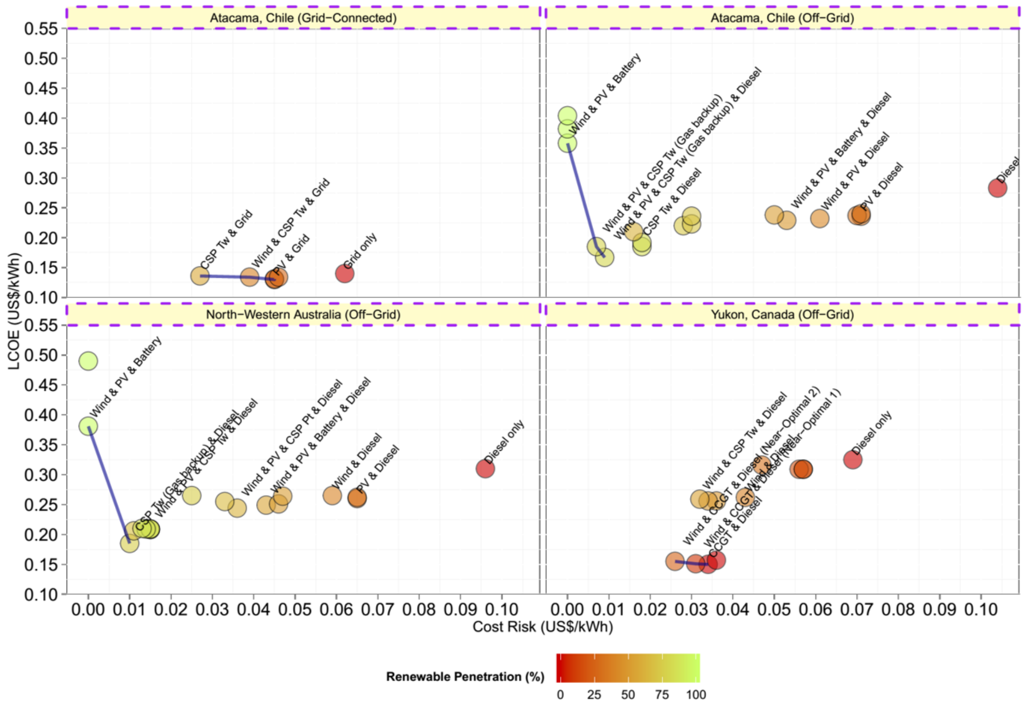


Figure 7.10 presents the key output of the portfolio theory: the comparison of unit cost and cost risk. The efficient frontier on this chart enables to identify the Pareto efficient portfolios. The Pareto efficiency refers to a state of allocation of resources in which it is not possible to improve one factor without making the other factor worse-off (Merton et al., 1972). In other words, the efficient frontier represents the points beyond which it is not possible to improve the cost without increasing the cost risk. For instance in the North-Australia mine, the Wind & PV & Battery portfolio has the same cost risk than the PV & Battery but features a lower unit price. The Wind & PV & Battery therefore represents the frontier of this LCOE level as it is not possible to reduce the LCOE without increasing the cost risk. Further observations on portfolio results are given as follow.

ATACAMA, CHILE (GRID-CONNECTED): The portfolio with CSP and grid power features the lowest level of fuel cost risk with $0.027/kWh due to a large share of renewable resources (i.e. 57%). The combination of PV and grid power presents the lowest cost of all portfolios and a cost risk of $0.045/kWh. Beyond those points, it is not possible to further improve the LCOE without increasing the cost risk. Interestingly, the grid-only alternative presents the highest level of cost risk with $0.062/kWh. As a consequence, the integration of renewable resources contributes to significantly reduce the fuel cost risk in this mine and while at the same time reducing the generation unit cost (compared to grid-only baseline).

ATACAMA, CHILE (OFF-GRID): Three portfolios present Pareto efficient characteristics in this mine. The first portfolio features 100% of renewable power with a combination of wind, PV, and battery. It is not possible to improve the cost risk factor at this point without increasing the LCOE. The second and third Pareto efficient portfolios include a mixture of wind, PV, and CSP power. One of these portfolio presents a slightly higher cost risk associated with small diesel backup capacities whereas the other portfolio has a lower cost risk due to the LNG share via the CSP backup boiler. The cost risk of both of these portfolios is also reduced due to the diversifying effect (i.e. diesel and LNG fuels). Again, the baseline with 100% of diesel-based generation presents the highest level of cost risk whereas low risk portfolios include large amounts of renewable capacities.

NORTH-WESTERN AUSTRALIA (OFF-GRID): Two portfolios are Pareto efficient in this mine. The first one combines wind, PV, and battery with no fuel backup capacities. The second one is the RQ1 least-cost portfolio featuring CSP, gas-backup, and diesel power. Similarly to the Chilean mine, the least-cost portfolio is associated with a very low cost risk due to a large share of renewable and a small diversifying associated with LNG and diesel fuels.

YUKON, CANADA (OFF-GRID): Three generation portfolios have been identified as Pareto efficient in this mine. Two of them involve a combination of wind, CCGT, and diesel while the third one features a CCGT and diesel plant with no renewable resources. These portfolios are all situated in the nearby area of $0.15/kWh for generation costs and between $0.026 and $0.034/kWh for cost risks. These results further stress that renewable alternatives can reduce the cost risk while providing near-optimal unit costs in this mine.

7.3.2 *Mine-life*

In this section, the impact of shorter mine-life periods on the LCOE is investigated in a portfolio approach. Shorter mine-life values have different impacts on the LCOE depending on the capital-intensity of a generation portfolio. This analysis is particularly relevant because RQ1 least-cost technologies tend to be extremely capital-intensive compared to baseline alternatives.

Figure 7.11: Unsymmetrical evolution of the LCOE in relation to mine-life

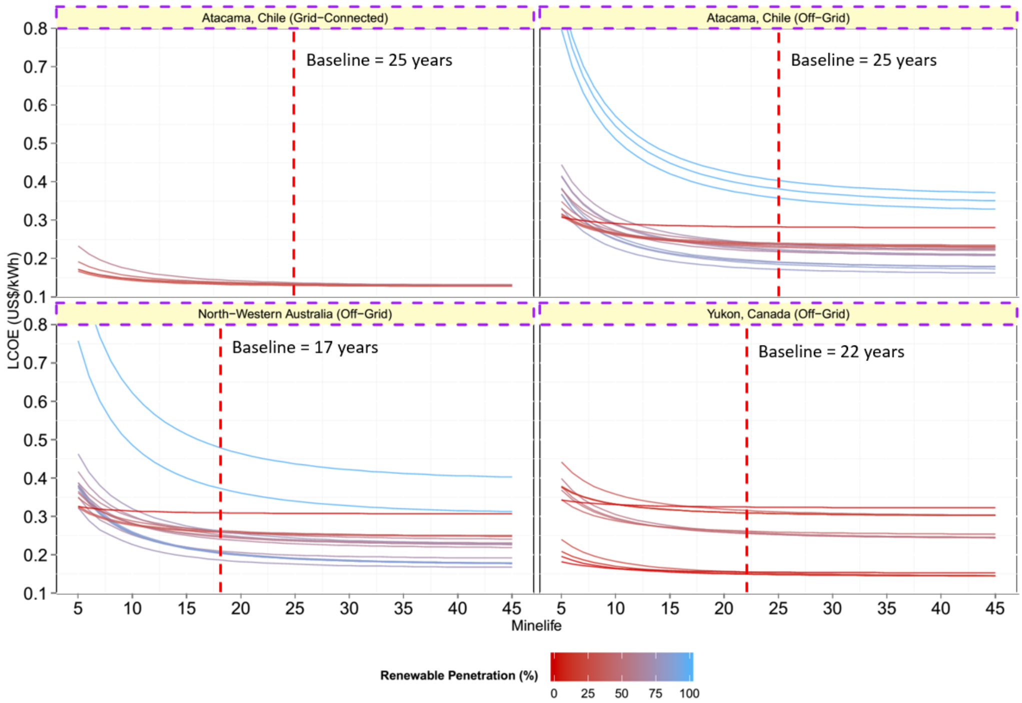
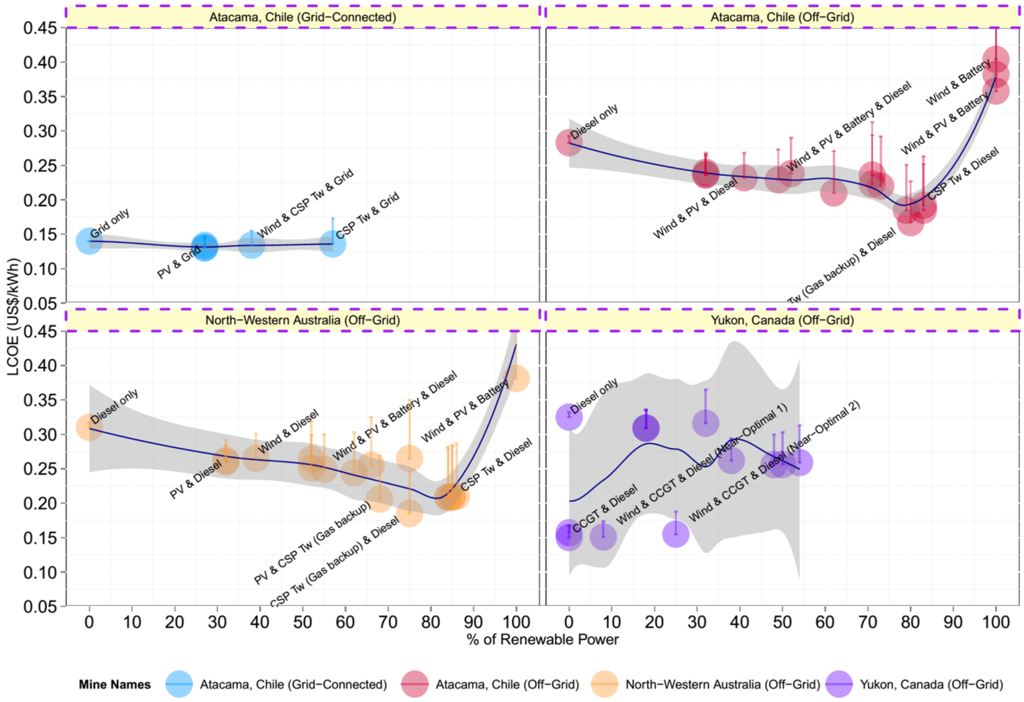


Figure 7.11 presents the changes in LCOE associated with different mine-life periods for all RQ1 portfolios. Two key observations can be made. On the one hand, generation portfolios with low renewable penetration are relatively insensitive to changes in mine-life for values between 5 and 45 years. This outcome is consistent with the sensitivity analysis of section 5.3.2.3 on page 138 in which fuel-intensive alternatives dominate the solution space of short mine-life periods. On the other hand, the impact of shorter versus longer mine-life periods on the LCOE involves unsymmetrical changes. Due to the discounting of future cash-flows (used to calculate levelised unit costs), shorter mine-life periods have a much greater impact than longer mine-life periods. The resulting distribution of LCOE is therefore not fitting a bell curve and is consequently incompatible with the requirement of the portfolio theory.

This issue is addressed by using the semi-variance, also called downside risk, in order to solely account for the risk of shorter mine-life periods. This metric calculates the standard deviation of the distribution based on positive cost risks only and consequently assumes that negative cost risks are symmetrical (i.e. normal distribution). The interpretation of the results should only be performed with respect to the downside risk (and not upside returns). The standard deviation of downside risk SD_d is calculated with $SD_d = \left[\sum_{i=1}^{m}(X - E(X))^2_{for\{X \leq E(X)\}}\right]^{\frac{1}{2}}$; where X is the expected LCOE for the expected mine-life and E(X) is the LCOE of a shorter mine-life [5]. Several past studies have demonstrated that the fundamental structure of the mean-variance theory is retained when the semi-variance is substituted for standard deviation to measure the cost risk (Hogan and Warren, 1974; Chong and Phillips, 2012).

Figure 7.12: Mine-life downside risk of generation portfolios (one standard deviation from the mean)

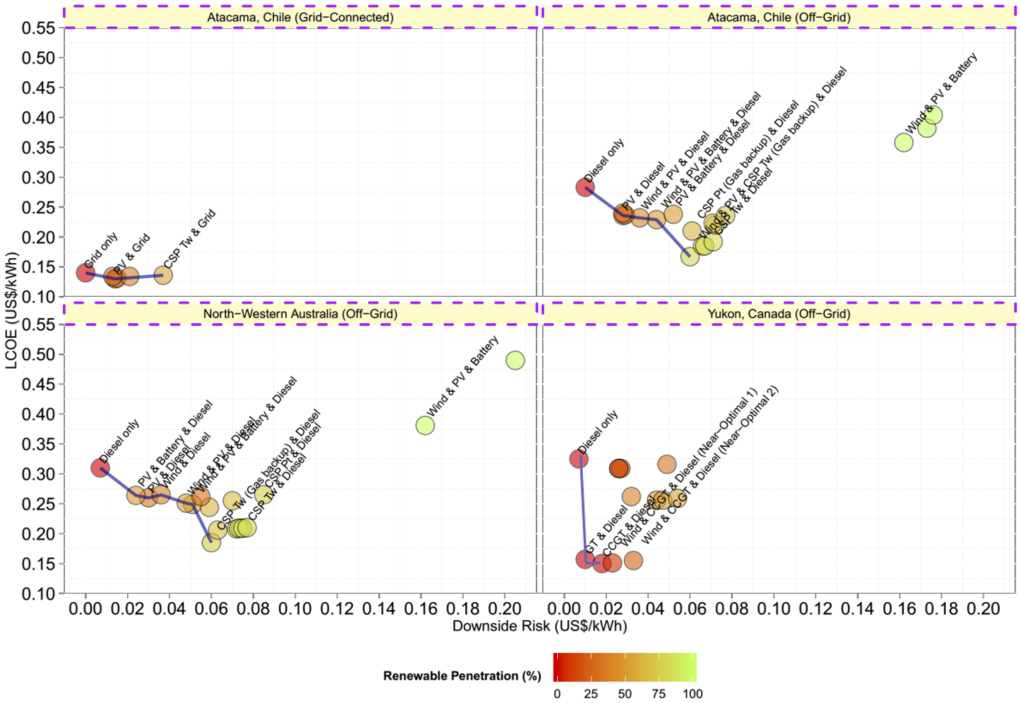


The downside risk of each generation portfolio is represented with error bars on figure 7.12. This result further suggests that high renewable penetration is associated with higher mine-life cost risk. Interestingly, the results of the mine-life cost risk are symmetrically opposed to the fuel cost risk - given in section 7.3.1 on page 189. Most risky technologies in terms of fuel cost risk are also the least risky technologies in terms of mine-life cost risk. This outcome is even more striking when looking at the efficient frontier in figure 5.18. All low-risk technologies (on the left of the x axis) are associated with baseline portfolios, i.e. 100% diesel or grid power.

A number of compromises between mine-life downside risk and unit cost can be found in the solution space of this portfolio analysis. Generation portfolios with no CSP plants form the major part of these compromises in Chilean and Australian mines. These portfolios typically include between 25 and 50% of renewable resources in their mix while the remaining power supply is obtained via diesel or grid power. These solutions balance both capital intensive and fuel intensive power alternatives in a generation portfolio. An-

[5] Note that there is no diversification effect associated with this cost risk as it is assumed that there is a perfect correlation between the investment periods of generation technologies in a given portfolio.

Figure 7.13: Efficient frontier for the mine-life cost risk



ecdotally, the gas turbine option is identified as Pareto efficient in the Yukon mine due to its lower capital cost and consequently lower mine-life cost risk - whereas the CCGT alternative is RQ1 least-cost portfolio (see table 5.1 on page 114).

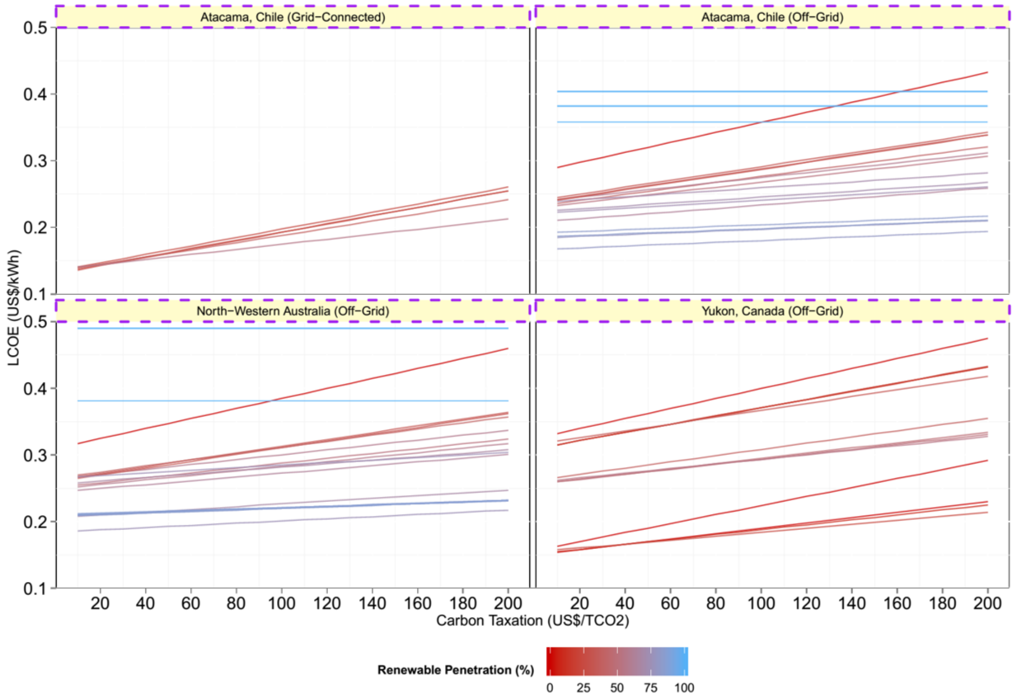
7.3.3 *Carbon Taxation*

Whereas the risk associated with fuel prices have been considered in section 7.3.1 on page 189, this analysis was solely based on historical prices with no carbon taxation. An additional risk should be therefore considered for carbon-emitting technologies. The impact of carbon taxation on the LCOE of generation portfolios is presented in figure 7.14. Similarly to the mine-life criterion, the cost risk of carbon taxation is calculated for the downside risk (as the baseline is a carbon price of $0/TCO$_2$).

These changes of carbon prices show different effects with respect to the amount of renewable resources. Portfolios that feature high renewable penetrations are relatively insensitive to changes in carbon taxation while the LCOE of fuel intensive portfolios are significantly increasing as the carbon price increases. A distribution of LCOE for carbon prices comprised between $0 and $200/TCO$_2$ was subsequently used to derive the cost risk associated with the potential of carbon taxation [6]. Another possible approach is to

[6] Because the choice for this range of carbon prices is relatively arbitrary, an additional analysis is performed in section 7.4.3 on page 204 for incremental carbon price levels.

Figure 7.14: Variation of the LCOE as a function of carbon price



model future carbon prices based on historical data. Despite that carbon policies have already been implemented for a number of years in some countries, there is not enough historical data available to significantly perform such forecast (Zhu et al., 2009) - see discussion section 8.3 on page 216.

Figure 7.15 presents the results of portfolio analysis in relation to the cost risk of carbon prices comprised between $0 and $200/TCO$_2$. Both the direction and the scale of these results are similar to the fuel price cost risk results. Yet, both of these effects are additive, which puts a greater risk on fuel intensive portfolios. The impact of the combination of all cost risks is subsequently considered in the following section.

7.3.4 *Overall Cost Risk*

It is assumed that the selected cost risks of this analysis are independent from each other. As a result, the three different cost risks can be added-up in order to calculate the total cost risk (Jansen et al., 2006). The error bars represented in figure 7.16 show the impact of the aggregated cost risks for different mine-life periods, fuel prices, and carbon prices. Interestingly, the total cost risk is not symmetrical around the expected LCOE. The downside risk is significantly higher than the upside risk as both mine-life and carbon taxation are only associated with negative returns (or positive cost risk).

Figure 7.15: Efficient frontier for carbon taxation cost risk

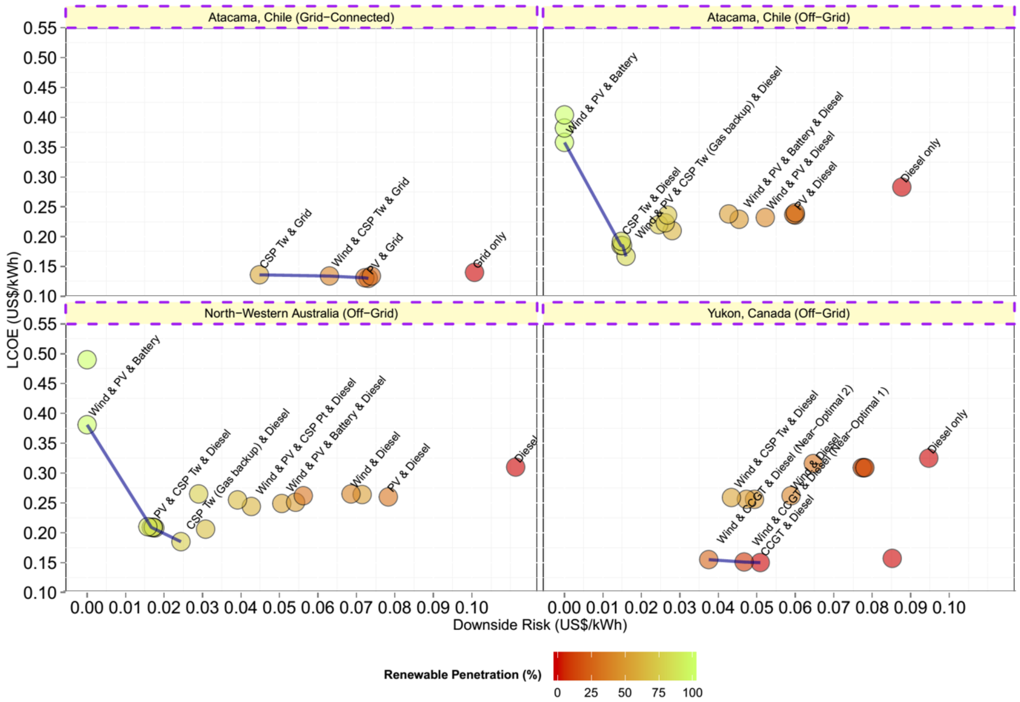


Figure 7.17 presents the results of the portfolio analysis with respect to the total cost risk [7]. Each generation portfolio has a risk of at least \$0.09/kWh, which represents a potential risk premium comprised between 40 to 50% of portfolio unit costs. Baseline portfolios (i.e. 100% diesel or grid power) have the highest cost risk values due to high cost risks for fuel and carbon prices (and despite a low mine-life cost risk).

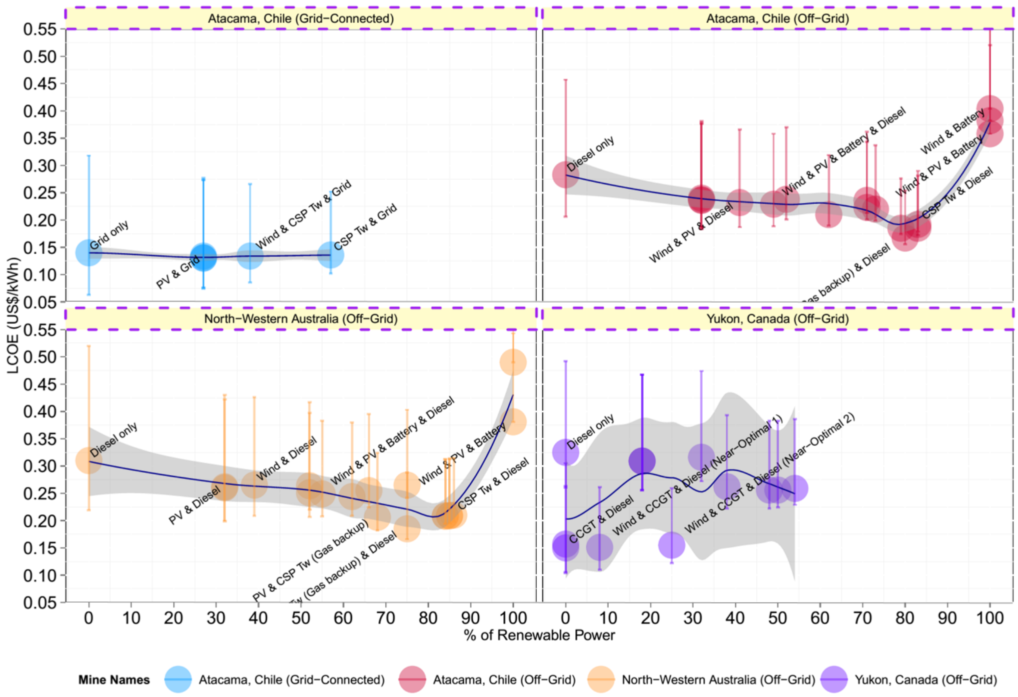
Low-risk portfolios feature high renewable penetration in all selected mining regions. Interestingly, least-cost portfolios of the Australian and Chilean off-grid mines are also the least-risk portfolios. As a result, no efficient frontier can be drawn for these mines (but rather an efficient point). Yet, different perspectives on each cost risk element can lead to different choices. These different outlooks on future input values are investigated in the following section.

7.4 DECISION-MAKING ANALYSIS

Whereas portfolio theory is useful to select a generation portfolio with minimal cost risk for a given unit cost, the portfolio framework is not providing insights on trade-offs between higher unit cost and lower cost risk. In other words, is it worth investing in a more expensive power system in order to reduce the cost risk? Furthermore, portfolio

[7] Because cost risks are aggregated, the scale of the x axis have higher values than in previous portfolio analyses

Figure 7.16: Total cost risk of generation portfolios



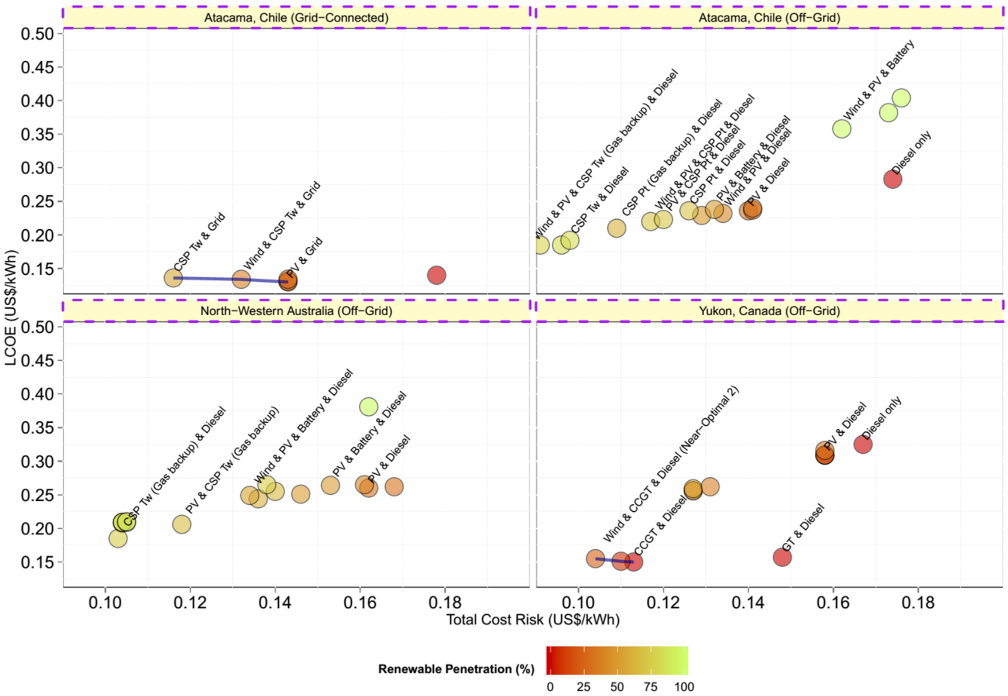
theory does not intrinsically consider different types of decision-makers. Some agents might be aiming at reducing the risk while others at reducing the expected cost. A decision-analysis is performed in following sections in order to tackle these issues, and further discussion points on decision-making are given in chapter 8 on page 213.

7.4.1 *Approach*

Arnold et al. (2002) have distinguished two types of agents: conservative and progressive. On the one hand, a conservative actor is an agent who focusses on the likelihood of being worse off as compared to his past situation. Conservative actors are further characterised as being opened to change only if the worst case scenario is improving the current situation. On the other hand, a progressive actor is an agent who is inclined to focus on changes that can improve his/her current situation, while ignoring the potential for states of nature that could be detrimental. These two behaviours are referred as pessimistic and optimistic decision-making.

As discussed in the literature review (see section 2.4 on page 33), the MaxiMin and MaxiMax principles can be used to describe both behaviours. In this research, the MaxiMin principle (i.e. pessimistic decision-making) considers the expected LCOE of each generation portfolio plus one standard deviation (i.e. cost risk), which is given by the

Figure 7.17: Efficient frontier for aggregated cost risks



portfolio analysis. Conversely, the MaxiMax (i.e. optimistic decision-making) is calculated by subtracting one standard deviation from the expected LCOE. In a nutshell, this approach provides a different economic ranking for each generation portfolio depending on whether the decision criteria is the downside or the upside risk, both risks being two distinct sides of the portfolio cost risk. This analysis is therefore both similar and different than the sensitivity analyses performed in section 5.3 on page 123. It is similar because it investigates the same parameter space and similar input changes. It is different because the results are based on given portfolios with given generation technologies and sizes - as opposed to RQ1 sensitivity analyses for which a new optimisation run was performed for each input change. In this analysis, the input changes do not affect the unit cost but it affects the risk associated with the unit cost. As a result, the focus of this analysis is on choosing the optimal generation portfolio among several portfolios in relation to a number of risk factors.

7.4.2 *Range of decisions*

A number of cost risks can be considered to rank the economic competitiveness of generation portfolios. In this research, the cost risk associated with mine-life, fuel prices, and carbon prices have been considered in a portfolio framework. The standard deviations of these risk factors are used here to determine the ranking of generation portfolios with respect to the MaxiMin and MaxiMax principles.

The following result tables present the different economic rankings for different perspectives on risk factors. The central scenario represents the RQ1 ranking (i.e. neutral perspective with no consideration of cost risk) whereas the MaxiMin and MaxiMax represent pessimistic and optimistic rankings. The rank of the least-cost portfolio for each risk criteria is highlighted in bold white. A number of combinations of risk factors are also presented in the right columns of the tables.

These risk-adjusted rankings are presented in table 7.1 on the next page and 7.2 on page 202. The first table presents the results of both grid-connected and off-grid Chilean mines while the second table focusses on the off-grid Canadian and Australian mines. Key observations are provided as follow.

Table 7.1: Range of potential decisions in Chilean off-grid and grid-connected mines

Mine Name	Generation Portfolio	US$/kWh				RANKINGS							
						MaxiMin					*MaxiMax*		
		LCOE	Fuel Cost Risk	Carbon Taxation Downside Risk	Minelife Downside Cost Risk	Pessimistic Fuel Price	Pessimistic Carbon Taxation	Pessimistic Minelife	Pessimistic Total	Central Scenario	Optimistic Fuel Price	Pessimistic Minelife And Optimistic Fuel Price	Pessimistic Minelife And Pessimistic Carbon Taxation
Atacama, Chile (Grid-Connected)	PV & Grid	0.13	0.05	0.07	0.01	3	3	2	3	1	2	2	3
	PV Tracking & Grid	0.13	0.05	0.07	0.02	4	4	3	4	2	3	3	4
	Wind & CSP Tw & Grid	0.13	0.04	0.06	0.02	2	2	5	2	3	5	5	2
	Wind & Grid	0.13	0.05	0.07	0.01	5	5	4	5	4	4	4	5
	CSP Tw & Grid	0.14	0.03	0.04	0.04	1	1	6	1	5	6	6	1
	Grid only	0.14	0.06	0.10	0.00	6	6	1	6	6	1	1	6
Atacama, Chile (Off-Grid)	Wind & PV & CSP Tw (Gas backup) & Diesel	0.17	0.01	0.01	0.06	1	1	1	1	1	1	6	1
	Wind & PV & CSP Tw & Diesel	0.18	0.01	0.02	0.07	2	3	3	2	2	9	11	3
	Wind & PV & CSP Tw (Gas backup)	0.19	0.02	0.02	0.07	3	2	2	3	3	4	8	2
	CSP Tw & Diesel	0.19	0.02	0.01	0.07	4	4	4	4	4	7	10	4
	CSP Pt (Gas backup) & Diesel	0.21	0.02	0.03	0.06	5	5	9	5	5	14	12	5
	Wind & PV & CSP Pt & Diesel	0.22	0.03	0.02	0.07	6	6	12	6	6	12	13	6
	PV & CSP Pt & Diesel	0.22	0.03	0.03	0.07	7	7	14	7	7	13	14	7
	Wind & PV & Battery & Diesel	0.23	0.05	0.05	0.04	9	9	10	9	8	8	7	9
	Wind & PV & Diesel	0.23	0.06	0.05	0.04	11	11	7	11	9	6	5	11
	PV & Diesel	0.24	0.07	0.04	0.03	12	10	5	10	10	2	2	10
	CSP Pt & Diesel	0.24	0.03	0.06	0.08	8	12	15	14	11	15	15	14
	PV Tracking & Diesel	0.24	0.07	0.06	0.03	13	13	6	12	12	3	3	12
	PV & Battery & Diesel	0.24	0.05	0.03	0.05	10	8	11	8	13	11	9	8
	Wind & Diesel	0.24	0.07	0.06	0.03	14	14	8	13	14	5	4	13
	Diesel only	0.28	0.10	0.09	0.01	17	16	13	15	15	10	1	15
	Wind & PV & Battery	0.36	0.00	0.00	0.16	15	15	16	16	16	16	16	16
	PV & Battery	0.38	0.00	0.00	0.17	16	17	17	17	17	17	17	17
	Wind & Battery	0.40	0.00	0.00	0.18	18	18	18	18	18	18	18	18

Table 7.2: Range of potential decisions in Canadian and Australian mines

		US$/kWh				RANKINGS							
						MaxiMin					*MaxiMax*		
Mine Name	**Generation Portfolio**	**LCOE**	**Fuel Cost Risk**	**Carbon Taxation Downside Risk**	**Minelife Downside Cost Risk**	Pessimistic Fuel Price	Pessimistic Carbon Taxation	Pessimistic Minelife	Pessimistic Total	Central Scenario	Optimistic Fuel Price	Pessimistic Minelife And Optimistic Fuel Price	Pessimistic Minelife And Pessimistic Carbon Taxation
Yukon, Canada (Off-Grid)	CCGT & Diesel	0.15	0.03	0.05	0.02	3	3	2	3	1	1	2	3
	Wind & CCGT & Diesel (Near-Optimal 1)	0.15	0.03	0.05	0.02	2	2	3	2	2	2	3	2
	Wind & CCGT & Diesel (Near-Optimal 2)	0.15	0.03	0.04	0.03	1	1	4	1	3	4	4	1
	GT & Diesel	0.16	0.04	0.09	0.01	4	4	1	4	4	3	1	4
	Wind & PV & Diesel	0.26	0.04	0.05	0.04	7	7	6	6	5	6	7	6
	Wind & PV & CSP Tw & Diesel	0.26	0.03	0.05	0.05	5	6	7	5	6	7	8	5
	Wind & CSP Tw & Diesel	0.26	0.03	0.04	0.05	6	5	8	7	7	8	12	7
	Wind & Diesel	0.26	0.04	0.06	0.03	8	8	5	8	8	5	5	8
	PV & Diesel	0.31	0.06	0.08	0.03	11	12	10	9	9	10	9	11
	PV Tracking & Diesel	0.31	0.06	0.08	0.03	10	10	12	10	10	11	11	9
	PV & CSP Tw & Diesel	0.31	0.06	0.08	0.03	12	11	11	11	11	9	10	10
	CSP Tw & Diesel	0.32	0.05	0.06	0.05	9	9	13	12	12	13	13	12
	Diesel only	0.32	0.07	0.09	0.01	13	13	9	13	13	12	6	13
North-Western Australia (Off-Grid)	CSP Tw (Gas backup) & Diesel	0.18	0.01	0.03	0.06	1	1	1	1	1	1	4	1
	PV & CSP Tw (Gas backup)	0.21	0.01	0.02	0.06	2	7	2	2	2	5	8	7
	Wind & PV & CSP Tw & Diesel	0.21	0.02	0.02	0.07	4	3	3	3	3	2	9	2
	PV & CSP Tw & Diesel	0.21	0.01	0.02	0.07	3	4	5	5	4	4	12	4
	Wind & PV Tracking & CSP Tw & Diesel	0.21	0.02	0.02	0.07	7	2	4	4	5	3	11	3
	Wind & CSP Tw & Diesel	0.21	0.01	0.02	0.07	6	6	6	6	6	6	14	5
	CSP Tw & Diesel	0.21	0.01	0.02	0.08	5	5	8	7	7	8	15	6
	Wind & PV & CSP Pt & Diesel	0.24	0.04	0.04	0.06	8	8	13	8	8	13	10	8
	Wind & PV & Battery & Diesel	0.25	0.04	0.05	0.05	11	11	11	9	9	11	7	9
	Wind & PV & Diesel	0.25	0.05	0.05	0.05	12	12	10	11	10	10	6	11
	PV & CSP Pt & Diesel	0.26	0.03	0.04	0.07	9	10	16	10	11	16	16	10
	PV & Battery & Diesel	0.26	0.05	0.06	0.05	13	13	15	13	12	14	13	13
	PV & Diesel	0.26	0.07	0.07	0.02	15	14	7	14	13	7	2	14
	PV Tracking & Diesel	0.26	0.07	0.08	0.03	16	16	9	16	14	9	3	16
	Wind & Diesel	0.27	0.06	0.07	0.04	14	15	12	15	15	12	5	15
	CSP Pt & Diesel	0.27	0.02	0.03	0.09	10	9	17	12	16	17	17	12
	Diesel only	0.31	0.10	0.11	0.01	18	18	14	17	17	15	1	17
	Wind & PV & Battery	0.38	0.00	0.00	0.16	17	17	18	18	18	18	18	18
	PV & Battery	0.49	0.00	0.00	0.21	19	19	19	19	19	19	19	19

ATACAMA, CHILE (GRID-CONNECTED): The least-cost portfolio of RQ1 (i.e. central scenario) is outranked by other portfolios when taking into consideration any of the selected risk factors - hence constituting a relatively fragile solution. On the one hand, both MaxiMin factors for fuel price and carbon taxation lead to an alternative portfolio (CSP and grid power). This alternative portfolio is associated with higher shares of renewable penetration and therefore presents lower cost risks for fuel and/or carbon prices. On the other hand, the grid only portfolio is favoured when considering a pessimistic outlook on the mine-life cost risk. In other words, a mining company with a pessimistic outlook on mine-life and neutral outlook on other factors would favour grid power over other alternatives.

ATACAMA, CHILE (OFF-GRID): The least-cost RQ1 central scenario remains the most competitive portfolio for all risk factors with the exception of one combination of risk factors. Interestingly, the optimal generation portfolio associated with a pessimistic outlook on mine-life combined with an optimistic outlook on fuel prices is composed of 100% of diesel power. This result implies that, under certain circumstances, it is more beneficial to solely use diesel power to power mining activities. The same combination of risk factors is also associated with an increasing competitiveness of portfolios that include PV, wind, and diesel power - whereas CSP-based portfolios tend to move down the ranking. Hence, the influence of risk preferences could lead to tremendous differences in the choice of the power system. Risk preferences of mining companies are subsequently discussed in chapter 8 on page 213 with respect to geological, financial, and societal risk factors.

YUKON, CANADA (OFF-GRID): Least-cost portfolios in this mine are either diesel/CCGT or wind/diesel/CCGT depending on the chosen risk perspective. Both the RQ1 central scenario and the optimistic perspective on fuel prices are associated with 100% fuel-based portfolios. The consideration of pessimistic risk factors for fuel and carbon prices lead to an uptake of wind power in the portfolio. This share of renewable power helps alleviating the risk of higher unit costs for CCGT and diesel power. Interestingly, the gas turbine portfolio is outranking the CCGT alternative when considering the mine-life risk factor. Capitally intensive technologies such as CCGT (as opposed to regular gas turbines) have lower unit costs but are more sensitive to shorter investment periods. Trade-offs between capital cost and investment period are therefore different depending on whether a pessimistic, neutral, or optimistic perspective is considered as mine-life risk criterion.

NORTH-WESTERN AUSTRALIA (OFF-GRID): The results for this mine are relatively similar to the off-grid Chilean mine. Under certain risk conditions, the optimal portfolio is shifting from high renewable penetration to 100% fuel-based. Portfolios including large shares of renewable resources tend to move up the ranking for pessimistic outlooks on fuel and carbon prices whereas portfolios with larger shares of fuel-based power tend to be more competitive when taking into account the mine-life criterion. Together, these risk factors lead to widely diverse solutions depending on the chosen risk perspective, and illustrate how risk factors can drive large shift in optima.

7.4.3 *Impact of carbon prices on decision-analysis*

The potential for new carbon policies in future years implies that fuel-intensive alternatives have a higher cost risk. This cost risk has been characterised by considering the time-series of portfolio unit costs for carbon prices comprised between \$0 and \$200/TCO_2. While the choice of these values is based on marginal price ranges for the next 20 years in decarbonisation pathways, it does not reflect historical time-series. In order to tackle this issue, an additional analysis is provided in tables 7.3 on the facing page and 7.4 on page 207 for incremental levels of carbon taxation. For obvious reasons, this analysis is only considering a pessimistic outlook on decision-making, i.e. carbon prices above \$0/TCO_2.

In the grid-connected Chilean mine, the optimal generation portfolio is shifting from PV/Grid to CSP/Grid for all carbon prices equal or above \$50/TCO_2. At this price level, the carbon emissions of the grid power generate a significant cost premium to the mine. This cost premium is largely reduced in portfolios with higher levels of renewable penetration[8]. In the off-grid Chilean mine, there is no significant shift in the ranking of least-cost portfolios. Because the RQ1 central scenario already includes 80% of renewable energy, the carbon taxation has no significant impact on the ranking of generation portfolios.

[8] Note that this evaluation is based on current levels of grid emissions. Changes in the grid generation mix would imply different cost premiums for carbon emissions.

Table 7.3: Range of potential decisions in relation to carbon prices (Chile)

Mine Name	Generation Portfolio	LCOE (US$/kWh)	Cost increment for different levels of Carbon Taxation (US$/kWh)					Central Scenario	*Ranking MaxiMin for different levels of Carbon Taxation*				
			$20/t	$50/t	$100/t	$150/t	$200/t		$20/t	$50/t	$100/t	$150/t	$200/t
Atacama, Chile (Grid-Connected)	PV & Grid	0.13	0.01	0.03	0.06	0.09	0.13	1	1	3	3	3	4
	PV Tracking & Grid	0.13	0.01	0.03	0.06	0.09	0.12	2	2	4	4	4	3
	Wind & CSP Tw & Grid	0.13	0.01	0.03	0.05	0.08	0.11	3	4	2	2	2	2
	Wind & Grid	0.13	0.01	0.03	0.06	0.09	0.13	4	5	5	5	5	5
	CSP Tw & Grid	0.14	0.01	0.02	0.04	0.06	0.08	5	3	1	1	1	1
	Grid only	0.14	0.01	0.04	0.07	0.11	0.15	6	6	6	6	6	6
Atacama, Chile (Off-Grid)	Wind & PV & CSP Tw (Gas backup) & Diesel	0.17	0.00	0.01	0.01	0.02	0.03	1	1	1	1	1	1
	Wind & PV & CSP Tw (Gas backup)	0.19	0.00	0.01	0.01	0.02	0.03	2	2	2	2	2	2
	Wind & PV & CSP Tw & Diesel	0.18	0.00	0.01	0.01	0.02	0.03	3	3	3	3	3	3
	CSP Tw & Diesel	0.19	0.00	0.01	0.01	0.02	0.03	4	4	4	4	4	4
	CSP Pt (Gas backup) & Diesel	0.21	0.00	0.01	0.02	0.04	0.05	5	5	5	5	5	5
	Wind & PV & CSP Pt & Diesel	0.22	0.00	0.01	0.02	0.03	0.04	6	6	6	6	6	6
	PV & CSP Pt & Diesel	0.22	0.01	0.01	0.02	0.03	0.04	7	7	7	7	7	7
	Wind & PV & Battery & Diesel	0.23	0.01	0.02	0.04	0.06	0.08	8	8	8	9	9	9
	Wind & PV & Diesel	0.23	0.01	0.02	0.04	0.07	0.09	9	9	11	11	11	11
	PV & Diesel	0.24	0.01	0.02	0.04	0.05	0.07	10	10	10	10	10	10
	CSP Pt & Diesel	0.24	0.01	0.03	0.05	0.08	0.10	11	12	12	12	12	12
	PV Tracking & Diesel	0.24	0.01	0.03	0.05	0.08	0.10	12	13	13	13	13	13
	PV & Battery & Diesel	0.24	0.01	0.01	0.02	0.03	0.05	13	11	9	8	8	8
	Wind & Diesel	0.24	0.01	0.03	0.05	0.08	0.10	14	14	14	14	14	14
	Diesel only	0.28	0.02	0.04	0.08	0.11	0.15	15	15	15	15	17	18
	Wind & PV & Battery	0.36	0.00	0.00	0.00	0.00	0.00	16	16	16	16	15	15
	PV & Battery	0.38	0.00	0.00	0.00	0.00	0.00	17	17	17	17	16	16
	Wind & Battery	0.40	0.00	0.00	0.00	0.00	0.00	18	18	18	18	18	17

As shown on table 7.4 on the facing page, the expected LCOE of the Yukon mine is sensitive to the risk of future carbon prices. Significant renewable uptake occurs when the risk of carbon taxation is equal or above $50/TCO$_2$. This shift in generation portfolio is taking place for wind generation only. Other renewable technologies have too high expected unit costs to be in the top ranking portfolios of this analysis. Interestingly, the risk of a carbon policy in Yukon is plausible as the Canadian government is considering to implement a $15CAD/TCO$_2$ across provinces. This price level is expected to increase year on year. Interestingly, the neighbouring province of British Columbia has already implemented a $30CAD/TCO$_2$ (Mildenberger et al., 2016).

Finally, in the Australian mine, the ranking of generation portfolios is insensitive to carbon prices for most portfolios. The second generation portfolio presents, however, a relative sensitivity to the risk of carbon prices equal or above $50/TCO$_2$ - due to 32 % of fuel-based power via the CSP gas-backup. This share of gas-backup is very high compared to other CSP-based portfolios, which therefore results in a significant cost risk associated with future fuel and carbon prices. Interestingly, a carbon price of $23AUS/TCO$_2$ was implemented in 2012 and then revoked in 2014. Yet, in this policy scheme, Australian-based mining companies received up to 95% of free carbon units in an effort to maintain the competitiveness of the industry (Jotzo, 2012). More recently, an emissions trading scheme was planned and almost immediately repealed by the Australian government. Further discussion elements on future carbon policies are given in section 7.19 on page 210.

Table 7.4: Range of potential decisions in relation to carbon prices (Canada, Australia)

Mine Name	Generation Portfolio	LCOE (US$/kWh)	Cost increment for different levels of Carbon Taxation (US$/kWh)					Central Scenario	*Ranking MaxiMin for different levels of Carbon Taxation*				
			$20/t	$50/t	$100/t	$150/t	$200/t		$20/t	$50/t	$100/t	$150/t	$200/t
Yukon, Canada (Off-Grid)	CCGT & Diesel	0.15	0.01	0.02	0.04	0.06	0.08	1	1	3	3	3	3
	Wind & CCGT & Diesel (Near-Optimal 1)	0.15	0.01	0.02	0.04	0.06	0.07	2	2	2	2	2	2
	Wind & CCGT & Diesel (Near-Optimal 2)	0.15	0.01	0.01	0.03	0.04	0.06	3	3	1	1	1	1
	GT & Diesel	0.16	0.01	0.03	0.07	0.10	0.13	4	4	4	4	4	4
	Wind & PV & Diesel	0.26	0.01	0.02	0.04	0.06	0.08	5	6	6	7	7	7
	Wind & PV & CSP Tw & Diesel	0.26	0.01	0.02	0.04	0.06	0.07	6	5	5	5	6	6
	Wind & CSP Tw & Diesel	0.26	0.01	0.02	0.03	0.05	0.07	7	7	7	6	5	5
	Wind & Diesel	0.26	0.01	0.02	0.05	0.07	0.09	8	8	8	8	8	8
	PV & CSP Tw & Diesel	0.31	0.01	0.03	0.06	0.09	0.12	11	10	10	11	11	11
	PV Tracking & Diesel	0.31	0.01	0.03	0.06	0.09	0.12	10	9	9	10	10	10
	PV & Diesel	0.31	0.01	0.03	0.06	0.09	0.12	9	11	11	12	12	12
	CSP Tw & Diesel	0.32	0.01	0.03	0.05	0.08	0.10	12	12	12	9	9	9
	Diesel only	0.32	0.02	0.04	0.07	0.11	0.15	13	13	13	13	13	13
North-Western Australia (Off-Grid)	CSP Tw (Gas backup) & Diesel	0.18	0.00	0.01	0.02	0.02	0.03	1	1	1	1	1	1
	PV & CSP Tw (Gas backup)	0.21	0.00	0.01	0.02	0.03	0.04	2	2	7	7	7	7
	Wind & PV & CSP Tw & Diesel	0.21	0.00	0.01	0.01	0.02	0.02	3	3	2	2	3	4
	PV & CSP Tw & Diesel	0.21	0.00	0.01	0.01	0.02	0.02	4	4	3	3	2	2
	Wind & PV Tracking & CSP Tw & Diesel	0.21	0.00	0.01	0.01	0.02	0.02	5	5	4	4	4	5
	Wind & CSP Tw & Diesel	0.21	0.00	0.01	0.01	0.02	0.02	6	6	5	5	6	6
	CSP Tw & Diesel	0.21	0.00	0.01	0.01	0.02	0.02	7	7	6	6	5	3
	Wind & PV & CSP Pt & Diesel	0.24	0.01	0.01	0.03	0.04	0.06	8	8	8	8	8	8
	Wind & PV & Battery & Diesel	0.25	0.01	0.02	0.03	0.05	0.07	9	9	9	10	11	11
	Wind & PV & Diesel	0.25	0.01	0.02	0.04	0.05	0.07	10	10	11	12	12	12
	PV & CSP Pt & Diesel	0.26	0.01	0.01	0.03	0.04	0.05	11	11	10	9	10	10
	PV & Diesel	0.26	0.01	0.03	0.05	0.08	0.10	13	14	14	15	15	15
	PV Tracking & Diesel	0.26	0.01	0.03	0.05	0.08	0.10	14	15	16	16	16	16
	PV & Battery & Diesel	0.26	0.01	0.02	0.04	0.05	0.07	12	12	13	13	13	13
	Wind & Diesel	0.27	0.01	0.02	0.05	0.07	0.09	15	16	15	14	14	14
	CSP Pt & Diesel	0.27	0.00	0.01	0.02	0.03	0.04	16	13	12	11	9	9
	Diesel only	0.31	0.02	0.04	0.08	0.11	0.15	17	17	17	18	18	18
	Wind & PV & Battery	0.38	0.00	0.00	0.00	0.00	0.00	18	18	18	17	17	17
	PV & Battery	0.49	0.00	0.00	0.00	0.00	0.00	19	19	19	19	19	19

7.5 SUMMARY

The cost risks associated with different factors of risk were investigated in this chapter. First, portfolio analysis has demonstrated that different risk factors have contrary effects on the expected unit cost. The risk factor associated with future fuel prices was found to clearly disadvantage portfolios with large shares of fuel-based power. Further, it was observed that diesel power has the largest cost risk among the selected power technologies of this research. Despite this risk level, diesel plants were found to have a negligible cost risk when solely used as backup capacity (i.e. low capacity factor and high unit cost) so as to maintain system adequacy at appropriate levels. Second, the risk of future carbon taxation was found to present similar effects to the risk associated with future fuel prices. Yet, this effect is limited to downside risk as there is no potential for negative carbon prices. Combined with the fuel price cost risk, these fuel-price related factors have the largest influence on expected unit costs. Third, the risk of shorter mine-life periods was found to have an opposite effect to fuel and carbon price risks. Generation portfolios with large shares of renewable power and small shares of fuel-based power are the most sensitive to the mine-life risk criteria. The capital intensity of such portfolios was found to be the underlying cause of this result. Therefore, the CSP-based portfolios, which were found to be cost optimal or near-optimal in three mines, can be seen as high risk from a mine-life perspective.

Together, these cost risks have been taken into consideration in a portfolio framework that characterises trade-offs between unit cost and cost risk. A number of Pareto improvements have been identified by this analysis. Cost risk can be improved by increasing the share of renewable penetration in three out of four mines. Yet, while the cost risk keeps diminishing with higher renewable penetration, the generation portfolios with more than 80% of renewable resources have much higher unit costs.

Further, it was highlighted that a decision-maker might consider each of these risks independently based on its attitude to risk or perspectives on context-specific elements. For instance, a mine with a high geological uncertainty might be more likely to exit or shutdown earlier than expected if the commodity price falls below the average cost (as discussed in section 8.2 on page 214). It was therefore argued that the consideration of each risk independently of each other might generate additional insights on the range of possible decisions - instead of one optimal solution. Subsequently, a decision-analysis was performed with respect to pessimistic and optimistic decision criteria on each risk factor.

Figure 7.18: Range of potential decisions in all selected mines

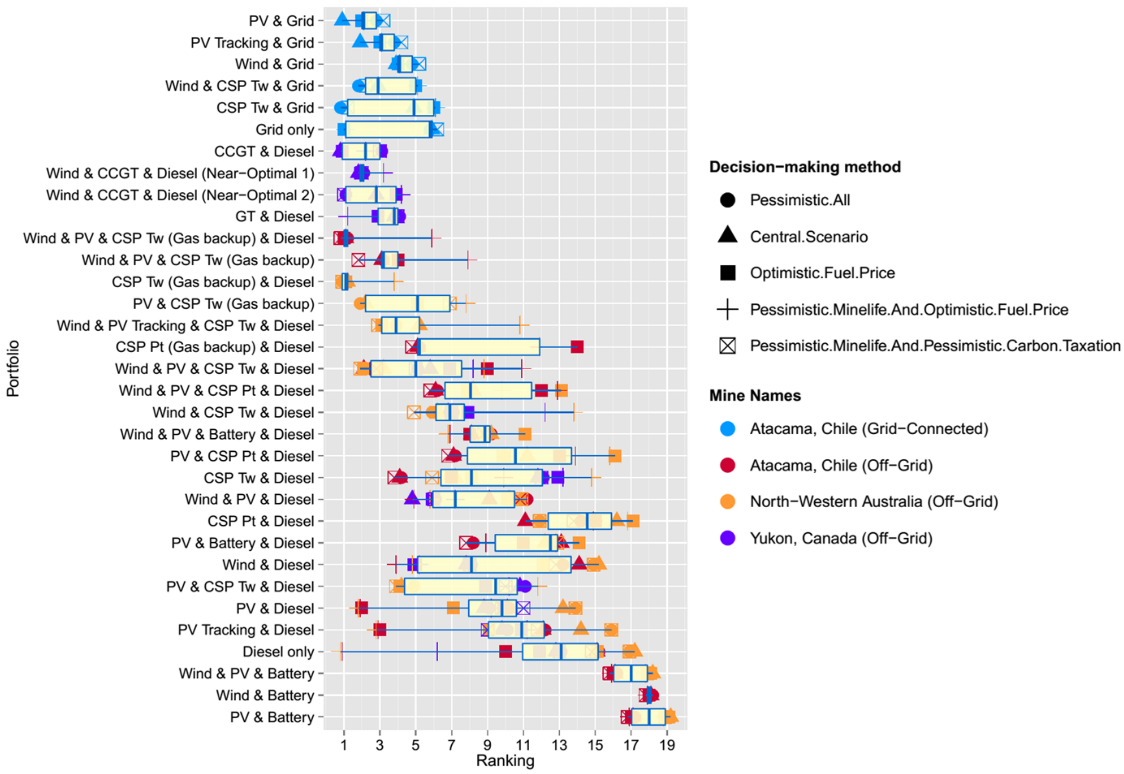
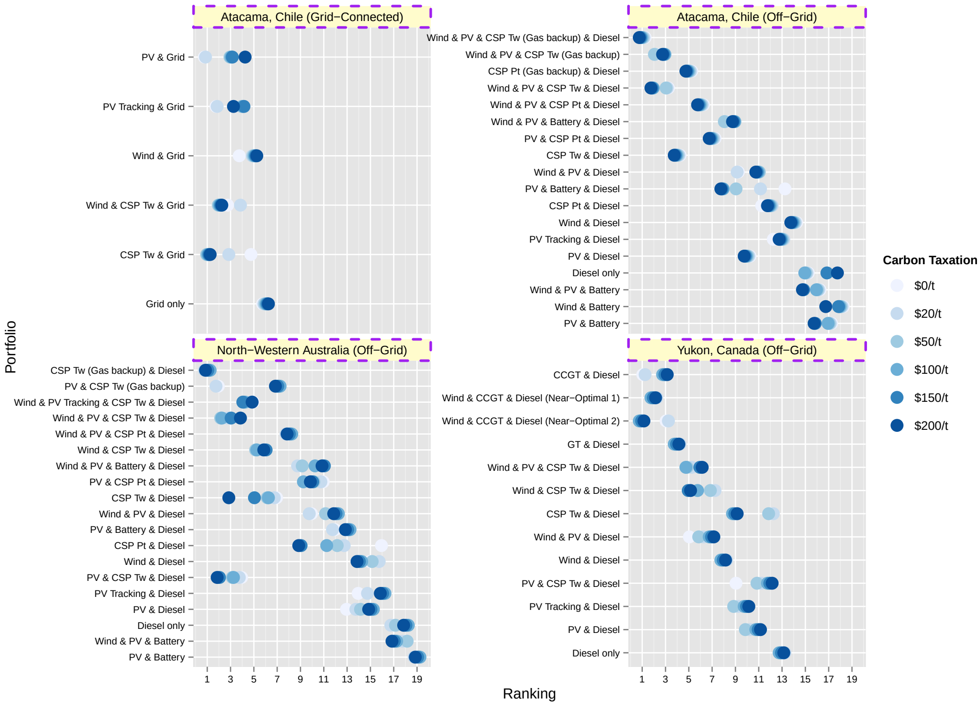


Figure 7.18 summarises the results of the decision-analysis. On average, RQ1 optimal results remain in the first quartile of ranking results for the Chilean and Australian off-grid mines - hence demonstrating the robustness of RQ1 results for these mines. Yet, while considering the entire decision space, it was found that the range of possible decisions is very different across the various generation portfolios. Specifically, the portfolios with 100% of diesel or grid power have the largest decision space. Those portfolios can viewed as optimal or worst solutions depending on the chosen risk perspective. Accordingly, a decision-maker with a positive outlook on fuel prices and a negative outlook on mine-life would favour fuel-based power systems. Conversely, portfolios with 100% of renewable power always remain at the bottom of the cost ranking independently of the chosen risk perspective.

An additional analysis was subsequently performed for incremental levels of carbon taxation. The results of this analysis highlighted that a number of renewable technologies can be viewed as economically optimal for carbon prices equal or above \$50/TCO_2. Figure 7.19 on the following page summarises the result of this analysis. The direction of changes in the economic ranking of this figure provides a number of insights. Specifically, portfolios with larger shares of renewable resources tend to move up the ranking as the expected carbon price increases. Yet, higher levels of carbon prices only affect top ranking portfolios in two mines: Chilean grid-connected and Yukon off-grid mines. In

Figure 7.19: Range of potential decisions in relation to different carbon prices



these mines, the unit cost of near-optimal portfolios are situated in the nearby areas of optimal portfolios. As a result, a change of carbon price has a more critical effect in these mines.

Finally, the results presented in this chapter have conclusively demonstrated that different perspectives on risks can lead to widely different choices. For instance, it was shown that a pessimistic perspective on future carbon taxation could generate an uptake of wind power in the Yukon mine whereas an optimistic outlook was solely associated with fuel-based technologies. The consideration of future energy policies has therefore the potential to critically impact the decisions of mining companies. These risks considerations will be discussed in the following chapter along with uncertainty factors.

Part IV

DISCUSSION

8

FUTURE WORK, LIMITATIONS, AND UNCERTAINTY FACTORS

8.1 OVERVIEW

The previous three chapters presented the results from the three research questions of this thesis, restated below:

1. To what extent can hybrid renewable power systems minimise electricity costs and reduce carbon emissions of the mining industry?
2. What is the optimal trade-off between capacity cost and reliability cost?
3. What is the influence of cost risks on the economics of such power systems?

Based on these research questions, the analyses carried out in previous chapters have provided insights on the economic competitiveness of hybrid renewable power systems associated with costs, reliability costs, and cost risks. It was specifically shown that hybrid renewable power systems can reduce significantly both generation costs and emissions but tend to be much more capital intensive, which implies higher risks from a mine-life perspective. Conversely, the capital intensity of hybrid renewable systems was shown to be associated with lower variable costs, which implies lower risks for changes in fuel and carbon prices. At the same time, more traditional generation alternatives, such as diesel or grid power, have proven to be much less capital intensive and less risky for shorter mine-life periods while presenting higher fuel and carbon price risks. This contrast between capital and fuel intensive alternatives has resulted in conflicting views in the decision-analysis.

Because different risk factors present serious implications for determining the optimal energy choice, a number of different risks and influencing factors are further investigated in this chapter and used as a way to frame the discussion and determine the future work. The following risk factors are discussed in this chapter:

1. Impact of geological and price uncertainty on mine-life risk,

2. Consideration of internal and mandated carbon prices,
3. Influence of alternative financing options on technological uptake,
4. Other influence factors.

The key areas of uncertainty are also provided at the end of the chapter along with a number of limitations on generalisation.

8.2 GEOLOGICAL AND OUTPUT PRICE UNCERTAINTIES

Past research has largely emphasised that one of the largest risks that mining operations are facing is the commodity price (Castillo and Dimitrakopoulos, 2014; Zhang et al., 2007; Albor Consuegra and Dimitrakopoulos, 2009). Whereas this risk has not been explicitly considered in the risk-analysis in chapter 7 on page 181, a proxy has been used instead: the mine-life period. Producer theory has described the relationship between mine-life and market prices from a short-run and long-run perspective. A mine can operate in the short-run while the commodity prices are below the average total cost as long as the variable costs are covered - otherwise the mine would experience a short-run shutdown. However, in the long-run, a mine facing extended periods in which commodity prices are below the minimum of the average total cost would lead to early market exit and generate significant exit costs. In this research, these exit costs are represented by the monetary valuation of the mine-life risk factor.

Because very large capital expenditures are required upfront for the construction of hybrid renewable power systems, these systems present higher mine-life risks than fuel-based alternatives. A decision analysis has taken into consideration this risk by accounting for the semi-variance of LCOE time-series with mine-life periods comprised between 5 and 45 years. This analysis has shown that in two out of four mines, the consideration of the mine-life risk factor leads to different optimal choices. Similarly, in section 5.3.2.3 on page 138, it was shown that 100% fuel-based alternatives become cost optimal for off-grid mines with a mine-life below 5 years and below 11 years in grid-connected mines.

Traditional evaluation methods in mining tend to deal with uncertainty by assuming an average case scenario, which tends to be chosen conservatively (Castillo and Dimitrakopoulos, 2014). A conservative approach might suggest that a positive NPV is expected much earlier than the end of the mine-life. Depending on the payback expectation, the choice of the power system could be different. Furthermore, the investment in capital intensive power systems that does not allow for flexibility in mine-life, makes it hard for mining managers to hedge against unfavourable market prices. As a consequence, the attitude and preferences of mining managers towards flexibility and payback expectation are of importance in the decision-making. It is therefore suggested that future work addresses this question with a qualitative interview-based approach. The characterisation of the attitudes and preferences of mining managers towards risks and flexibility would provide additional insights to assess future uptake levels.

This issue is also closely related to geological uncertainty. Mines that face high geological uncertainty have a mine-life expectancy that is predicted with a significant error margin - which means that the most conservative decisions are more likely to be taken (i.e. fuel-based or low levels of renewable penetration). Dowd (1994) has shown that one of the most sensitive variables in mining projects is the ore reserve. He further demonstrated that the ore reserve should be treated as a function of the commodity price. Because the cost of mining depends, *inter alia*, on the grade and tonnage of the mining reserve, the market prices determine the minimum ore grade that is required to cover the costs. Market price and ore reserves are among the most important factors to assess mine-life risk. Yet, both factors can never be accurately known in advance. The amount and grade of the ore reserve estimation depends on the quality of the samples taken, as well as the accuracy of the extrapolation method used to calculate the depletion rate. Because the ore reserve is depleted over time, the rate of depletion is used as a basis to extrapolate the mine-life. Dowd further characterises the risk factors associated with early market exit by stating that "one of the most significant factors in mine failures is the inability to meet forecast grades and tonnages".

This research has used a relatively parsimonious approach to model mine-life risks but a number of other approaches have been considered in past studies in order to characterise both geological and price uncertainties. For instance, Castillo and Dimitrakopoulos (2014) have applied a direct block simulation (DBSim) to model uncertain geological grades and commodity prices. Their research suggests that traditional evaluation methods tend to underestimate the size of the final pit, which potentially lead to revenue losses. Yet, they recognise that their findings are limited by the sole consideration of a single pit, processing, and stockpiling method. In the same line of argument, Albor Consuegra and Dimitrakopoulos (2009) have proposed a simulated annealing algorithm to determine the equally probable realisation of mineral deposits. They have shown that deterministic evaluations of ore bodies can lead to overestimating the NPV by approximately 10% and the mine-life by one year.

Alternatively, Zhang et al. (2007) have presented a reactive modelling approach that emulates optimal responses to changes in market prices at each new period. This approach suggests that the NPV of the mine can be maximised by incorporating optionality and flexibility in mining project evaluation. McCarthy and Monkhouse (2002) have applied a real option model to determine the economic viability of a copper mine with respect to commodity prices and variability of ore grade and tonnage. Interestingly, this study suggests a diminishing discount rate over time in order to account for the risk saturation effect. They further suggest that the long-run forward curve should be applied to discount future cash flows in conjunction with a real option model. This approach is, however, limited to the decision of opening or closing an existing mine - and does not consider new mining projects.

Together, these alternative approaches to assess commodity and geological uncertainties highlight that different levels of sophistication can be used to value risk and mine-life. The semi-variance was used in this thesis to determine the mine-life cost risk. In other words, this thesis focused on the sensitivity of unit costs to shorter mine-life values. The most sensitive generation portfolios were presented as high risk from a mine-life perspective. Yet, these high risk portfolios were found to present the lowest unit costs in many cases. Because capital intensive portfolios show great economic potential, the risk associated with long mine-life periods should be further investigated in order to account for geological specificities.

8.3 CARBON PRICES

Two types of carbon prices could be considered in risk analyses: company-based or policy-based. The company-based approach implies that mining firms use an internal carbon prices to assess investment decisions. This approach is usually used both as part of risk management strategies in order to mitigate the risk of future carbon policies and as a mean to identify low-carbon investment alternatives. Such internal or mandated policy is associated with a major risk: carbon leakage. Hence, because of its impact on marginal costs, carbon leakage might eventually favour one country over another, which will eventually shift the geographical source of a fraction of the production - so as to avoid carbon taxation. Yet, a recent World Bank publication has reported that to date this phenomenon has not materialised on a significant scale (Kossoy et al., 2015). Policy design components have helped to mitigate this issue by using a range of measures such as free allocations, exemptions, border adjustments, and rebates. Further, this risk is diminishing as more and more countries are adopting carbon pricing measures.

Carbon pricing measures have been considered in this thesis with respect to different levels of carbon price. Whereas the carbon price is mandated or internal to the mining companies has not been specified as both measures would lead to identical outcomes - if considered in a financial model. Specifically, it was found in section 7.4.3 on page 204 that carbon prices as low as $10/t$CO_2$ lead to different generation portfolios in the Chilean grid-connected mine, and $50/t$CO_2$ in the Yukon mine. This latter case is particularly interesting as it is not economically viable to implement renewable power in this mine without a carbon price - or a change in capital cost or fuel price. Alternatively, it was shown in the decision-analysis in section 7.3.3 on page 195 that the implementation of carbon measures is a significant risk to the mine, and this risk is increasing as higher fractions of fossil-fuel are included in the power mix. Accordingly, the uptake of renewable power is therefore dependent on two carbon-related factors: a mandated carbon-policy or the risk of a mandated carbon-policy. The latter can be either considered by implementing an internal carbon price that reflects the risk or by including carbon risk in investment models.

Similarly to the ore reserve or commodity price uncertainties, the future level of carbon prices cannot be known. Two analyses have been performed in this thesis to incorporate this risk: the consideration of the semi-variance of LCOE time-series for carbon prices comprised between $0 and $200/t$CO_2$, and the consideration of incremental carbon price levels from $20 to $200/t$CO_2$ (scenario-based). The former provided insights on generation portfolios that are the most sensitive to carbon taxation while the latter described the changes in optimal generation portfolios for different carbon price levels. Similarly, Zhu et al. (2009) have applied a scenario-based approach to model carbon prices and determine optimal outcomes. They applied a Monte Carlo approach to determine the upper and lower bounds of different portfolios costs. While their method was slightly different to the one applied in this thesis, the rationale is identical: because there is not enough historical data on carbon prices, the favoured approach is to assess different scenarios. These different scenarios can provide useful insights on cost sensitivity and tipping points. For instance, portfolios that are the most sensitive to a small change in carbon price present a much higher risk, probabilistically speaking. For instance, wind power is included in the optimal mix for a carbon price of $10/t$CO_2$ in the Chilean grid-connected mine. If a carbon policy is planned, such a small carbon price is likely to be in effect soon-after the policy is implemented. Conversely, the risk associated with high carbon prices is arguably less likely to be part of the near future. Accordingly, even though carbon prices cannot be probabilistically modelled, the consideration of current and planned carbon policies provides interesting insights for the decision-analysis.

In the mining regions that are considered in this thesis, a number of trends can be observed in relation to carbon and environmental policies. For instance, a provincial tax of $CAD15/t$CO_2$ is currently being planned in Canada and a tax of $US5/t$CO_2$ is being implemented in Chile for thermal plants with a capacity of 50MW or more. While these taxation levels are not high enough to significantly change the optimal technological mixes that are presented in this thesis, it is expected that those carbon prices will increase year on year. Subsequently, current and planned policies might significantly influence decision-makers to include a fraction of renewable resources in the mix - in order to hedge off the carbon price risk. In section 5.3.1.5 on page 133, it was identified that the most sensitive base cases relate to the Chilean grid-connected mine and the Yukon mine, whereas the base cases of the Australian and Chilean off-grid mine are robust solutions with respect to carbon policies (i.e. insensitive to changes in carbon price). In all logic, the carbon risk should be at least considered for the most sensitive solutions in order to optimise decisions and reduce the opportunity cost. Yet, the long-run carbon prices cannot be probabilistically predicted without historical data. Instead of using probabilities, the characterisation of the attitude of investors towards risk as well as the content of mining sustainability strategies could provide valuable insights that could inform a decision framework.

The carbon disclosure project from the World Bank has shed light on these sustainability strategies in the report "Putting a price on risk: Carbon pricing in the corporate world" (2015). It reported that 435 companies have implemented internal carbon pricing to offset the risk of future carbon regulations in 2015, up from 150 firms in 2014. A number of mining and energy companies, which are high carbon emitters, have adopted this approach - including Anglo American, Teck Resources, Canadian Oil Sands Limited, Suncor Energy, Enbridge, or Statoil. This internal price of carbon fluctuates between $4 and $150/t$CO_2$ between firms, and reflects a wide variety of risk perspectives among energy and mining corporations. The dominating driver behind this approach is that carbon pricing can help mitigating risk and identifying potential long-term investment opportunities. Accordingly, the findings of this report signal a major point: carbon pricing is now part of the cost of doing business and is included as a standard line item in budget assumptions of mainstream businesses. Whereas the mines considered in this research are not part of these companies, such internal carbon pricing is nonetheless an appropriate method to value a hypothetical carbon regulation. The level at which such internal price should be set at is, of course, the main area of uncertainty. As a consequence, mining and energy companies would benefit from more certainty on future environmental regulations in order to reduce the risk associated with low-carbon investments, especially for the most capital intensive alternatives.

8.4 FINANCING AND POLICY-INCENTIVES

The sensitivity analysis on discount rate given in 5.3.2.1 on page 135 has shown that renewable-based portfolios are less competitive as the nominal discount rate increases. It was found that CSP-based systems are viable for discount rates comprised between 10 and 14%. In the Yukon mine, wind power was found to be economically viable for a discount rate equal or below 8%. Overall, it was shown that discount rates above 14% are not economically compatible with energy storage and CSP plants. As a consequence, different discount rates can have tremendous consequences for the future uptake of renewable generation alternatives.

The discount rate is often defined as a measure of the cost of capital, which is determined by considering risk premiums, interest rate, investment period, and tax implications (Short et al., 2005). Better financing conditions can help reduce the cost of capital, which would therefore improve the competitiveness of renewable alternatives[1]. Mendelsohn et al. (2012) have found that guaranteed loans from public institutions have historically improved the financing conditions of renewable projects. Specifically, their study shows that the cost of two CSP projects was reduced by 17% under a loan guarantee scheme. Interestingly, this study also suggests that the financing conditions tend to improve as the technology matures and as the experience of the energy developer develops. That is, as the most complex technologies mature, the perceived risk - represented by the interest yield - is set to decline. Yet, well capitalised mining companies might already have the opportunity to use their financial strength to absorb a fraction of the project risk and put pressure on capital providers to improve financial conditions and yields.

Alternatively, a number of policy instruments (i.e. tax incentives, accelerated depreciation schedule) have also been used by some countries to reduce the cost of renewable projects. Typically, such policy schemes require that either the developer, the investor, or the single-owner have sufficient taxable income to benefit from the tax or depreci-

[1] A number of additional financing arrangements have been reviewed in section 3.6.5.2 on page 64.

ation incentives. A number of complex financial structures have subsequently arisen in order to take advantage of these tax credits. Yet, Harper et al. (2007) suggest some these financial schemes might present too much complexity for investors because simplicity, standardisation, and speed of the financing method were found to be of high importance in selecting a financial scheme. In the selected countries of this PhD research, a number of these incentives are currently in place for renewable projects (KMPG, 2014).

In Canada, the government has committed to reduce GHG emissions by 17% by 2020 (from 2005 levels) and that 90% of the power generation be produced without GHG emissions by 2020. As a consequence, Canada has implemented several incentives at the provincial and federal scale, including:

- Accelerated Capital Cost Allowance (ACCA): provides depreciation advantages for clean energy sources and energy conservation.
- Canadian Renewable and Conservation Expense (CRCE): allows developers to deduct a fraction of the renewable project expenses from the taxable basis or transfer the tax benefits to investors under a flow-through mechanism.
- Scientific Research & Experimental Development Program (SR&ED): encourages Canadian companies to carry out research in the clean energy field through Investment Tax Credit (ITC) - which can represent a cash refund of up 35% of the investment.
- Diverse mechanisms focusing on specific energy technologies and biofuels such as ecoENERGY (biofuel and renewables), Carbon Capture and Storage Fund, Alberta Quota Obligation, or Ontario Feed-in Tariff.

In Australia, an emission trading scheme and a carbon pricing structure have recently been cancelled or repealed. Yet, a number of alternative measures are still in place to incentivise the uptake of renewables.

- Regional Australia's Renewable Program: includes two mechanisms (I-RAR, CARRE) that offer support to off-grid and island energy systems and promote knowledge sharing.
- Clean Energy Finance Corporation (CEFC) & Renewable Energy Venture Capital Fund: offer complementary financing for renewable energy projects.
- R&D Tax Incentive: offers tax offset for renewable energy development and R&D activities.
- Feed-in tariff: several state-based initiatives exist for small renewable projects - but there is no country-based feed-in tariff.

In Chile, the government has pledged to reduce emissions by 20% by 2025, which is expected to materialise into an average of 650MW of new renewable capacity per year over ten years. A number of energy policies and tax regulations have been subsequently implemented in order to achieve the carbon target as well as increase fuel security and attract foreign investment.

- Non-Conventional Renewable Energy Law (NCRE): mandates that energy producers incorporate a quota of at least 5% of renewable energy in their mix, directly or indirectly. Renewable power generated in grid-connected mines would qualify as an indirect contribution to this quota. An increase of 0.5% per year of the renewable quota is set to take place between 2015 and 2020. A fine of $28/MWh is applied for non-compliant producers.
- Grants for feasibility studies (National Energy Commission): provide up to 50% of the feasibility cost with a maximum of 5% of the estimated project cost.
- Open market access: Chile guarantees access to transmission lines with no discretionary exclusions. No regulatory barriers are in place, which allows both foreign and national companies to compete on the power market.

However, a recent study published by Nasirov et al. (2015) on the Chilean energy market has shown that those measures have had a limited effect on the advancement of renewable technologies. This study suggests that grid constraints, processing time, and limited access to financing are among the main barriers that have historically limited the uptake of renewable technologies in Chile.

To conclude, a number different mechanisms are currently in place in the selected countries of this study. Because financing conditions are intricately linked with unit cost and risk, such incentives have the potential to alter the economics of hybrid renewable power systems. Whereas the consideration of these different schemes is out of the scope of the present study, it is suggested that future work should take into consideration the impact of these policy instruments on mining generation costs.

8.5 OTHER INFLUENCING FACTORS

A number of additional influencing factors have been identified in the literature. On the one hand, the social acceptance of mining projects has been seen in past studies as being critical in order to speed-up the development process and avoid shutdowns due to public opposition (Davis and Franks, 2011). On the other hand, Boyse et al. (2014)

suggest that powering local communities would impact the formal licence because it would help expediting the permitting process for new mines. As a consequence, the impact of power alternatives on the length and success rate of the permitting process could be an additional consideration to investigate in future research.

Additional influencing factors that are of interest for future studies include the impact of renewables on market value, low yields financing programs for developing countries (e.g. UNDP, World Bank), and the impact of economic uncertainty on strategic decision-making in global mining firms.

8.6 AREAS OF UNCERTAINTY

Whereas previous sections have discussed the different factors that influence decision-making, this part focuses on the uncertainty associated with the unit costs that are given in this study in section 5.1 on page 114. These costs are given by the optimisation model HELiOS-Mining, which relies on different types of uncertain parameters and data inputs and consequently introduces output uncertainty. In addition, different input values can potentially alter the results and point to different conclusions.

Two key categories of uncertain data inputs are of major importance in this thesis: demand and supply. The demand input to HELiOS-Mining relates to the expected power demand for each mine. Different patterns of energy demand could potentially lead to different results. For instance, CSP alternatives are especially interesting for mining activities because of both the high power demand at night time and low cost of heat storage. Different day/night demand patterns would mean that other technologies might provide more benefits than CSP alternatives and therefore alter the results of this research. Because the mining power demand is based on continuous processes, there are little changes in demand that can take place outside of intensity changes - which would only imply that the sizing of the system should be linearly adjusted. Demand shifting initiatives can also alter the demand pattern in order to improve the convergence between power demand and intermittent resources - either through process re-engineering or by using existing storage options. Demand shifting was investigated in this thesis and it was suggested that little economic improvements can be realised with such initiatives but further research are required to investigate this issue (as discussed in section 5.3.2.2 on page 137).

The second and arguably the most uncertain category of input variables relates to the supply side, which includes technical parameters and economic variables. Uncertain technical factors include efficiency (especially for part-loading), outage rates (forced and planned), emission intensity, and lifetime. Uncertain economic variables include capital costs, maintenance and operation costs, fuel and carbon prices, and cost of capital. As shown in section 5.3.3 on page 140, the use of different cost estimates can lead to different outputs and therefore constitutes a major area of uncertainty. The rapidly declining cost of renewable alternatives is one of the main reasons for cost uncertainty. For instance, the cost of PV plants was first estimated at $1900/kW in 2013 and then at $1200/kW in 2016, which represents a reduction of 37% over the three years of this PhD. Other key areas of uncertainty are given as follow.

- Resource availability: The output of renewable resources over time is unknown for all intermittent alternatives. An adequacy analysis has been performed in 6 on page 163 in order to investigate the impact of this uncertainty. Whereas the historical or probabilistic worst-case scenarios have been used in this analysis, there is no guarantee that more extreme events do not take place in future years, especially considering climate change uncertainties. Yet, such extreme events would have a limited impact on the results of this thesis as most systems include enough redundancy to handle long periods with no or little renewable resources - as shown in figure 6.4 on page 179.
- Time-resolution: Consideration of sub-hourly supply patterns (i.e. ramp-up rates, intra-hour resources, and start-up time) have not been modelled due to the hourly time scale of HELiOS-Mining. This limitation is expected to have a relatively limited impact because diesel backup can be used as spinning reserve to balance the system - current low-speed diesel plants can be part-loaded with 10% or lower of the power capacity, as shown in Sebastian (2009). Frequent start-ups of power plants are another area of uncertainty as they can reduce the plant lifetime. Typically, each start-up costs 10 hours in technical life expectancy for gas turbines (DEA, 2012). Both ramp-up rates and start-up costs could be considered in future work on a minute by minute basis for a limited number of power systems - this is unlikely to be feasible for the full range of results given in section 5.1 on page 114 due to the computational requirements associated with such high resolution modelling.
- Grid extension: Specific topological studies have not been conducted to value the cost of grid-extension for off-grid mines. Such studies are particularly difficult to perform for off-grid mining contexts (e.g. mountainous, remoteness, lack of data).

If such study is to be performed in the future, the unit cost of both base cases presented in 5.1 on page 114 can be used as proxy to compare the cost of grid-extension against off-grid systems, which would in turn provide a characterisation of the economic viability of grid-extension alternatives.

- Reliability: Stochastic simulations for power security were not conducted as enough contingency reserves (i.e. modular diesel or grid capacity) were included in power systems to balance forced outages (see section 4.5.1 on page 96). In addition, different maintenance strategies have different consequences on the availability rates of each power plant. A detailed characterisation of these consequences has not been conducted and therefore constitutes another area of uncertainty.
- Emissions: Modelling of part-load emission performance and different types of diesel plant (i.e. low/medium/high speed) was not performed [2], which implies that the emission intensity of each generation portfolio given in appendix A on page 263 might be understated in some instances.
- Temporal efficiency losses: Considerations for different icing losses at different times/seasons of the year for wind turbines have not been included. This limitation would be especially interesting to consider if different de-icing or anti-icing technologies were to be assessed against their respective economic competitiveness. Similarly, the efficiency losses associated with sand or dust on PV or CSP modules have not been modelled, which constitutes another area of uncertainty.
- Learning rate: The cost estimates that were used in HELiOS-Mining represent another major area of uncertainty. There is a consensus in current research and market studies that a cost reduction of most renewable technologies is to occur in both short and long-term - as discussed in the sensitivity analyses on capital costs in section 5.3 on page 123. Because this learning rate cannot be accurately forecasted, it constitutes another area of uncertainty.
- Wind speed: The extrapolation method to calculate wind speed at different wind hub heights introduces some output uncertainty. Neutral air flow stability is assumed in this thesis but further studies would be required to assess the shape of terrain and the stability of the air flow. Combined with in-situ measurements, performing such study would reduce the output uncertainty of wind power plants.

The following uncertainties are associated with a number of technological characteristics that have not been considered in current work and might influence the cost estimates

[2]Note that part-load performance curves are taken into consideration by HELiOS-Mining for fuel efficiency.

presented in table 5.1 on page 114. The consideration of these characteristics in future work might alter the results given in this thesis, and therefore constitutes another area of output uncertainty.

- Heat: CSP, CCGT and gas turbine alternatives can provide low-grade heat. For instance, CSP can typically provide heat at up to 350°C, which could be used as heat booster to alleviate a fraction of the heat demand (Hu et al., 2010). The combination of heat and power in hybrid renewable power systems is a key area of interest for future work as it might significantly improve the economic viability of several generation alternatives.
- Water desalination: Large CSP plants are often located in arid or semi-arid areas (like many mining locations) and could be used for cogeneration to support water desalination. Low-pressure steam could be extracted from the power block in order to run multi-effect distillation (MED) stages. This process is likely to be the most efficient for high temperature levels, such as those provided by CSP towers (Philibert, 2010). Such analysis has been neglected in this study but is of interest for future work - especially for developing countries in which there is a scarcity of fresh water.
- Fuel types: Whereas biogas and biodiesel have been considered in section 5.3.1.5 on page 134, a number of additional biomass alternatives could be considered. A report of IRENA (2012a) suggests that the LCOE of biomass-fired power plants varies between \$0.06 and \$0.29/kWh depending on capital expenditure and fuel cost. These technologies can provide additional benefits for industrial firms that produce biomass wastes (e.g. pulp and paper mills or sugar mills). However, if there is no such industrial wastes, the cost of these alternatives can become relatively high in remote locations, due to the high transportation costs associated with the low energy density of biomass. Accordingly, most of the biomass used in power production comes from local sources. Because of the remote nature of most mining activities, the availability of such resources widely varies from mine to mine. Both the Chilean and Australian mines are located in arid locations and have limited availability of biomass. The Yukon mine has access to significant wood resources and could be a candidate for biomass-fired power plants. However, a recent report has assessed that such project might be challenging because it would require the approval of several stakeholders, i.e. forest managers, local communities, regulators (Yukon-Government, 2016). Biomass regulations for the Yukon province are to

be developed in future years, which might provide new energy opportunities for Yukon's mining industry.

Finally, the interaction between uncertainties is an additional area of uncertainty. An example of such interaction is the technological learning rate and the fuel prices. An increase in the learning rate for renewable systems is to produce a significant shift in the demand curve of fossil-fuel, which according to microeconomic theory is typically leading to a decrease of the wholesale price. Combined with the potential of new carbon policies and resource uncertainty, such interactions between variables are a source of output uncertainty. These interactions can be handled in an optimisation model by setting correlation coefficients between variables - such as in section 7.7 on page 189. Yet, the characterisation of the appropriate covariance coefficients between variables is another area of uncertainty.

8.7 LIMITATIONS ON GENERALISATION

The results of this thesis can be generalised while taking into consideration three major limitations: geographical region, industrial activity, and mine-life. First, the results given in this thesis can be applied to neighbouring mines that have similar climate characteristics - and therefore similar resource inputs. Second, generalisation to other mines can only be performed for mining activities based on continuous processes that require a constant power load (e.g. non-ferrous metals) and given similar capital costs, discount rate, and fuel/carbon prices (sensitivity analyses in section 5.3.3 on page 140 and 5.3.1 on page 126 can be consulted for dissimilar costs and price inputs). Further, the value of foregone production (VFP) in RQ2 is mine specific - as it is calculated based on ore grade and total revenue - and is therefore likely to be different for neighbouring mines. As a result, RQ2 results are valid for mines with similar VFP values whereas the sensitivity analysis 6.4.1 on page 176 can be used for different VFP values. Similarly, RQ3 results can be generalised given that the mine of interest is located in one of the three mining regions of this thesis and has a constant power demand. Finally, it was shown that results varied significantly with respect to different mine-life values. The sensitivity analysis 5.3.2.3 on page 138 should be consulted if the mine of interest has a different mine-life.

Some results may be partially generalisable to other regions. For instance, some mining regions in Africa have similar solar resources but dissimilar wind patterns. Further, the sensitivity analysis on discount rate (in section 5.3.2.1 on page 135) should be consulted for mining regions with significant political risk in order to account for the relevant risk-adjusted discount rate (as well as the sensitivity analysis on fuel prices in section 5.3.1 on page 126). The list of limitations and research uncertainties should also be consulted (section on page 222) before generalising results to other mines.

Whereas this chapter has focused on limitations and future work, the following conclusion chapter summarises the findings along with the contributions of this research.

9

CONCLUSION

The conclusion chapter is used to summarise the findings of each research question along with the main research contributions of this PhD thesis. Future work, research limitations, and potential for generalisation are stated in chapter 8 on page 213. Research gaps are reviewed in section 2.5 on page 37 with respect to past literature.

9.1 RESTATEMENT OF THE RESEARCH PROBLEM

At the time this PhD research was started, there was ambiguity and uncertainty in the mining industry on whether it would be economically beneficial to implement hybrid renewable power systems in off-grid mines. After reviewing the literature in chapter 2 on page 17, it appeared that the cost of renewable hybridisation and energy storage was particularly unclear, especially considering the context-specific characteristics of the mining industry (as reviewed in section 2.5 on page 37 on research gaps). The issue of least-cost system configuration was therefore the subject of research question one in chapter 5 on page 109.

The second area of interest subsequently emerged from the literature review: should an hybrid renewable power system be 100% reliable, or is it more economical to undersize the system in order to reduce the capital costs (hence reducing reliability)? Based on the value of lost load of the mining industry, the issue of reliability cost was tackled in the second research question in chapter 6 on page 163.

Hybrid renewable power systems also face problems over amortization. Mining time-frames are not always compatible with the lifetime required to recover the investment. Due to mine-life uncertainty, mining companies might not be willing to invest in capital-intensive technologies (as opposed to fuel-intensive) even if there is a potential for long-term profit. Yet, fuel-intensive technologies present additional risks such as the potential for higher than expected fuel and carbon prices. Subsequently, the trade-offs between the cost risk of capital-intensive technologies and fuel-intensive power technologies were assessed against mining operational risks in the third research question on page 181.

These research problems were tackled with a novel modelling approach that combines engineering (technology explicit modelling), economics (investment model, price forecasting, valuation of foregone production), and finance (portfolio theory, decision-analysis) in order to investigate the research problem from multiple perspectives (see section 9.3 on page 236 on research contributions). This research focused on three predominant mining regions, including: grid-connected and off-grid mining in Northern Chile as well as off-grid mining in North-Western Australia and Yukon, Canada (as detailed in section 4.1 on page 91). The main findings of this PhD are summarised as follow.

9.2 SUMMARY OF FINDINGS

9.2.1 *Research question 1 (RQ1):*

To what extent can hybrid renewable power systems minimise electricity costs and reduce carbon emissions of the mining industry? Based on technological and sizing optimisation of system costs, the following key findings were identified [1] in chapter 5 on page 109 in order to answer RQ1:

1. Hybrid renewable power systems can provide significant economic benefits in three of the four mines analysed in this research - as shown on figures 9.1 on the next page and 5.1 on page 114. Specifically, it was found that life-cycle cost savings of up to 57% and carbon savings of up to 82% can be generated with such systems (against diesel or grid baselines) - see section 5.2 on page 113.
2. Least-cost renewable portfolios are associated with total life-cycle carbon savings of 2.7MtCO_2 in the Chilean grid-connected mine, 7MtCO_2 in the Chilean off-grid mine, 9MtCO_2 in the Yukon off-grid mine, and 1.2MtCO_2 in the Australian off-grid mine (against diesel or grid baselines; as given in table 5.3 on page 125). Further carbon reductions can be achieved through the implementation of carbon policies (section 5.3.1.5 on page 133), lower financing rates (sections 5.3.2.1 on page 135 and 8.4 on page 219), and capital cost reductions (section 5.3.3 on page 140).

[1] Detailed technological configurations are provided in appendix A on page 263.

Table 9.1: Summary of key results across four mines and three mining regions

Atacama, Chile (Off-Grid)

Technological configurations	LCOE (US$/kWh)	% Renewable	TLCC Savings	CO_2 Savings
Wind & PV & CSP Tw (Gas backup) & Diesel	0.167	80%	41%	82%
Wind & PV & CSP Tw (Gas backup)	0.185	79%	33%	82%
Wind & PV & CSP Tw & Diesel	0.185	83%	34%	83%
CSP Tw & Diesel	0.192	83%	32%	83%
CSP Pt (Gas backup) & Diesel	0.210	62%	26%	66%
Wind & PV & CSP Pt & Diesel	0.220	73%	22%	73%
PV & CSP Pt & Diesel	0.223	71%	21%	71%
Wind & PV & Battery & Diesel	0.229	49%	19%	49%
Wind & PV & Diesel	0.232	41%	19%	41%
PV & Diesel	0.236	32%	17%	32%
CSP Pt & Diesel	0.236	71%	16%	71%
PV Tracking & Diesel	0.237	32%	16%	32%
PV & Battery & Diesel	0.238	52%	16%	52%
Wind & Diesel	0.240	32%	15%	32%
Diesel only (Baseline)	0.283	0%	0%	0%
Wind & PV & Battery	0.358	100%	-15%	100%
PV & Battery	0.382	100%	-26%	100%
Wind & Battery	0.404	100%	-30%	100%

Atacama, Chile (Grid-Connected)

Technological configurations	LCOE (US$/kWh)	% Renewable	TLCC Savings	CO_2 Savings
PV & Grid	0.130	27%	7%	27%
PV Tracking & Grid	0.131	27%	6%	27%
Wind & CSP Tw & Grid	0.134	38%	4%	38%
Wind & Grid	0.134	27%	4%	27%
CSP Tw & Grid	0.136	57%	3%	57%
Grid only (Baseline)	0.140	0%	0%	0%

Optimal mix including CSP Power

Optimal mix with no CSP Power

Baseline mix

Yukon, Canada (Off-Grid)

Technological configurations	LCOE (US$/kWh)	% Renewable	TLCC Savings	CO_2 Savings
CCGT & Diesel	0.150	0%	57%	47%
Wind & CCGT & Diesel (Near-Optimal 1)	0.151	8%	57%	51%
Wind & CCGT & Diesel (Near-Optimal 2)	0.155	25%	55%	60%
GT & Diesel	0.157	0%	53%	10%
Wind & PV & Diesel	0.256	48%	21%	48%
Wind & PV & CSP Tw & Diesel	0.256	50%	21%	50%
Wind & CSP Tw & Diesel	0.259	54%	20%	54%
Wind & Diesel	0.262	38%	20%	38%
PV & CSP Tw & Diesel	0.309	18%	5%	18%
PV Tracking & Diesel	0.309	18%	5%	18%
PV & Diesel	0.309	18%	5%	18%
CSP Tw & Diesel	0.316	32%	3%	32%
Diesel only (Baseline)	0.325	0%	0%	0%

North-Western Australia (Off-Grid)

Technological configurations	LCOE (US$/kWh)	% Renewable	TLCC Savings	CO_2 Savings
CSP Tw (Gas backup) & Diesel	0.185	75%	40%	68%
PV & CSP Tw (Gas backup)	0.206	68%	32%	59%
Wind & PV & CSP Tw & Diesel	0.208	84%	33%	84%
PV & CSP Tw & Diesel	0.209	85%	32%	85%
Wind & PV Tracking & CSP Tw & Diesel	0.209	84%	32%	84%
Wind & CSP Tw & Diesel	0.209	85%	32%	85%
CSP Tw & Diesel	0.210	86%	32%	86%
Wind & PV & CSP Pt & Diesel	0.244	62%	22%	62%
Wind & PV & Battery & Diesel	0.249	55%	20%	55%
Wind & PV & Diesel	0.251	52%	20%	52%
PV & CSP Pt & Diesel	0.255	66%	18%	66%
PV & Diesel	0.260	32%	16%	32%
PV Tracking & Diesel	0.262	32%	16%	32%
PV & Battery & Diesel	0.264	52%	15%	52%
Wind & Diesel	0.265	39%	15%	39%
CSP Pt & Diesel	0.265	75%	14%	75%
Diesel only (Baseline)	0.310	0%	0%	0%
Wind & PV & Battery	0.381	100%	-16%	100%
PV & Battery	0.490	100%	-53%	100%

CSP Tw = CSP Tower   CSP Pt = CSP Parabolic Trough

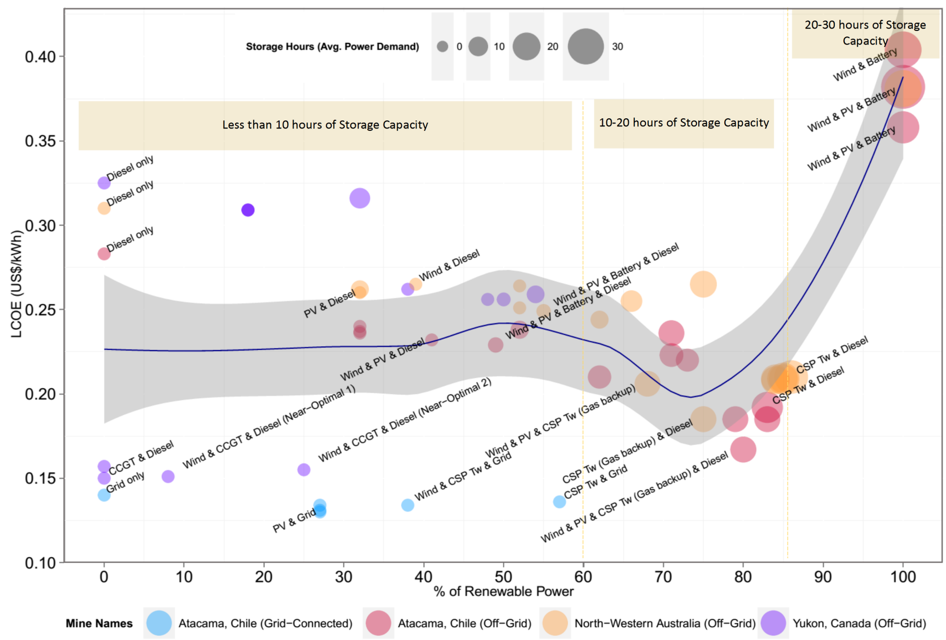
3. CSP power systems dominate the solution space in off-grid mines for Chile and Australia (including seven and eight of the first eighteen solutions respectively). The low storage costs of CSP systems were found to provide significant benefits over other storage alternatives for mining contexts - as detailed in the section on renewable integration on page 118. However, the capital costs of CSP plants in base cases (in table 5.3 on page 125) were found to be 65% higher than no-CSP alternatives. Hence, the trade-offs between capital-intensive and fuel-intensive alternatives were subsequently investigated in RQ3.

4. Grid-connected mines have relatively smaller opportunities for implementing hybrid renewable power systems than off-grid mines - with respect to the Chilean mining context. Specifically, the optimal scenario features 27% of renewable power in the Chilean grid-connected mine whereas it reaches 80% in off-grid settings - as shown in table 9.1. Further analyses on different grid constraints are given in section 5.3.1.3 on page 130.

5. Least-cost system configuration in the Yukon mine was found to be 100% fuel-based using CCGT and diesel power. Yet, two near-optimal alternatives were identified that incorporate a significant share of wind power - as shown in table 9.1. These configurations were categorised as key opportunities in terms of cost risk in the third research question - i.e. trade-offs between unit cost and cost risk of future fuel prices (see chapter 7 on page 181).

6. Power systems featuring a renewable penetration comprised between 60 and 85% of total capacity have optimal or near-optimal costs in three out of four mines - (see section 5.2.2.1 on page 118). LCOE is sharply increasing to uneconomical levels for 100% of non-dispatchable renewable power, and such power configuration requires between 20 and 50 hours of battery capacity in order to handle different patterns of intermittency without fuel-based backup power - as shown on figure 9.1.

Figure 9.1: LCOE of all optimal and near-optimal technological mixes



7. There is a synergic interaction between the number of power plant types contained in a single hybrid power system and the system cost. Technological configurations with the largest number of resource types present the lowest generation costs - as detailed in section 5.2.2.2 on page 120.
8. Most sensitive optimal solutions were identified for the Chilean grid-connected mines and the off-grid Yukon mine (as shown in table 5.4 on page 158). Highest elasticity values for these mines are associated with fuel prices, discount rate, and reduction of capital costs. On the contrary, the Chilean and Australian off-grid mines are characterised by less sensitive solutions based on CSP plants complemented by fuel-based power and non-dispatchable renewable resources.
9. Demand-shifting was found to negligibly impact the LCOE and the optimal amount of renewable resources in all selected mines - as detailed in section 5.3.2.2 on page 137.

10. Future scenario analyses in section 5.4 on page 148 show that larger shares of renewable resources are hedging off the risk associated with future fuel price variations. Power systems with smaller shares of renewable resources are much more sensitive to variations of fuel and carbon prices. It is suggested that different perspectives on future prices and carbon policies could lead to different solutions. Hence a decision-analysis is subsequently performed in the third research question in chapter 7 on page 181.

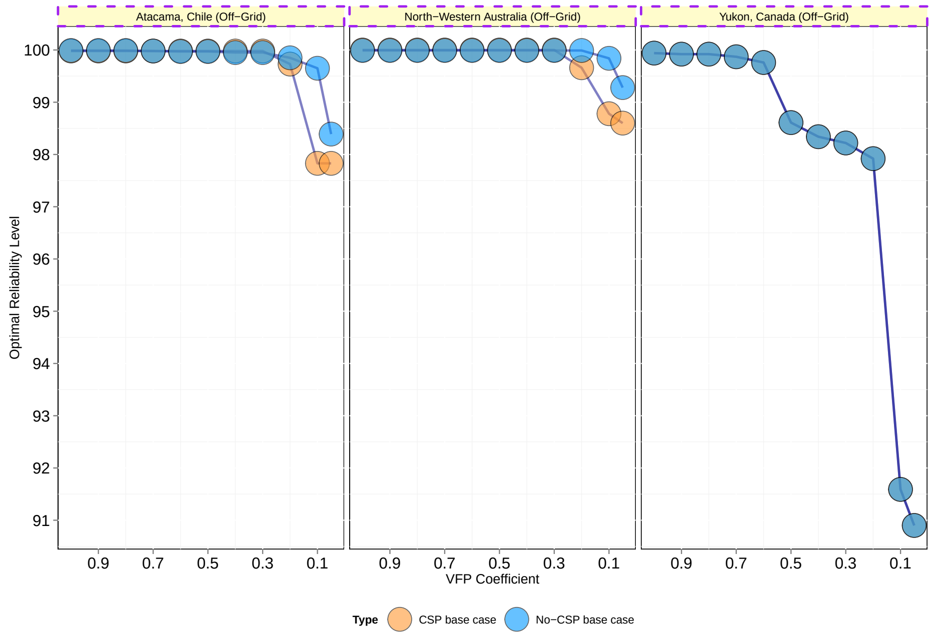
9.2.2 *Research question 2 (RQ2):*

What is the optimal trade-off between capacity cost and reliability cost? The worst case climate scenario (hence presenting different patterns of intermittency) and the value of lost load were combined in order to determine the optimal level of reliability with respect to RQ1 results in chapter 6 on page 163. Key findings include:

1. Optimised hybrid renewable power systems that include both fuel-based and renewable power in the mix are able to perfectly cope with different climate scenarios (hence maintaining a reliability index of 100%; as shown in section 6.3 on page 168). At the same time, the average unit cost of these portfolios increases by 2% to 5% when accounting for the economic impact of the worst case climate scenario.
2. Reliability indices are relatively insensitive to variations in renewable resources due to the large fuel-based capacities in RQ1 results. CSP-based power systems have the largest backup capacities due to high outage rates and non-modularity of the CSP power block - see section 6.3 on page 168.
3. Hybrid renewable power systems with 100% of renewable inputs (and no or little fuel-based backup capacity) have the lowest cost when the reliability value is comprised between 93 and 98% so as to economically balance reliability costs and system benefits. This outcome demonstrates that reliability values lower than 100% can provide economic benefits only if no fuel-based resources are included in the mix (using VFP base assumptions). However, these systems present much higher unit costs than hybrid power systems that do include fuel-based power in the mix - see section 6.3 on page 168.
4. Fuel-based capacities provide benefits to the generation mix in all mines, even at low capacity factors (as shown in figure 6.5 on page 180). Specifically, it was shown

that the unit cost of diesel power is significantly lower than the value of foregone production (VFP) of all mines for genset capacity factors higher than 2.4%.

Figure 9.2: Optimal reliability level as a function of the value of foregone production



5. Reliability values below 100% become economically viable for VFP reductions of 50 to 90% from base assumptions (for generation portfolios that combine renewable and fuel-based power) - as shown in figure 9.2. Mines with such VFP values would generate economic benefits by shutting down the production at times of low renewable resources. See section 6.4 on page 176 for further details.

9.2.3 *Research question 3 (RQ3):*

What is the influence of cost risks on the economics of such power systems? This last research question was investigated in chapter 7 on page 181 using a portfolio approach. Key findings include:

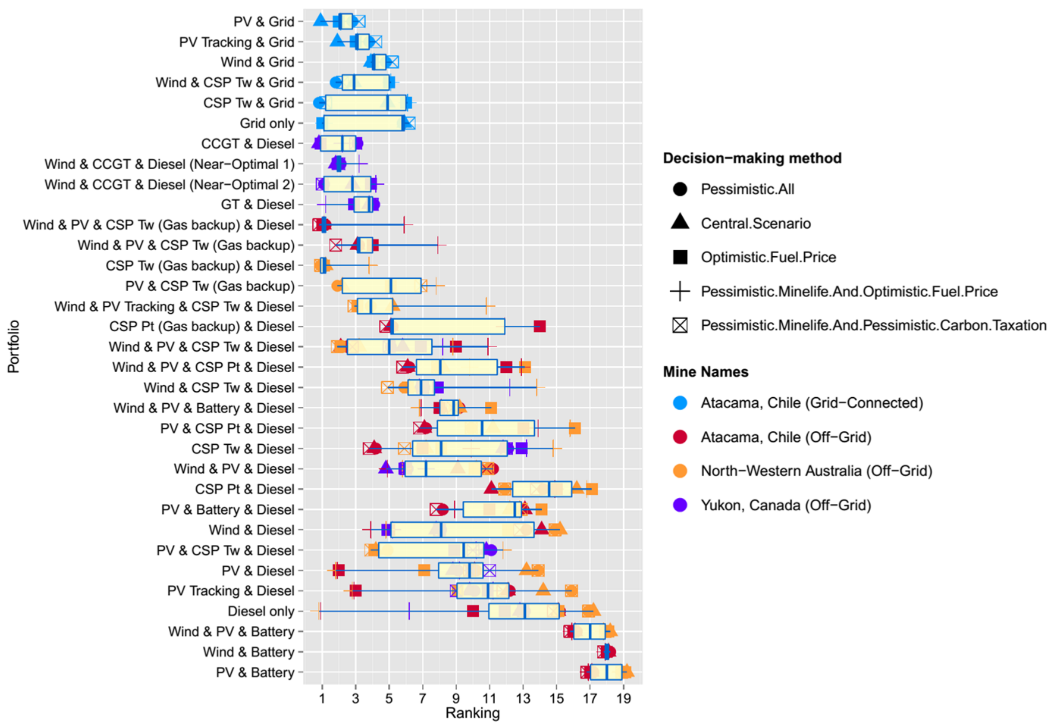
1. Portfolio analysis has demonstrated that each generation portfolio is associated with a total cost risk of at least $0.09/kWh, which represents a potential risk premium comprised between 40 to 50% of the portfolio unit cost.
2. Portfolios with 100% diesel or grid power have the highest cost risk values. While these portfolios have been characterised as low risk from a mine-life perspective (due to their low capital intensity), they present the highest risk in terms of fuel and carbon price variation.

3. Different risk factors have contrary effects on the expected unit cost - as shown in section 7.3 on page 188. Portfolios featuring large shares of fuel-based power have higher fuel and carbon prices cost risks. On the contrary, high renewable portfolios tend to have a larger mine-life cost risk.

4. CSP-based portfolios, which are cost optimal in two mines and present opportunities for three mines, are characterised as high risk from a mine-life perspective whereas the no-CSP portfolios featuring high levels of fuel-based power present higher risks from a fuel and carbon price perspective.

5. Scenario-based analysis of carbon prices demonstrated that several renewable alternatives become economical for carbon prices equal or above \$50/TCO_2 in the off-grid Yukon mine and the Chilean grid-connected mine (in section 7.4.3 on page 204). Yet, the decision ranking of portfolios with larger shares of renewable resources tend to move up as the expected carbon price increases in all selected mines.

Figure 9.3: Range of potential decisions in all selected mines



6. Risk perspectives have a significant impact on decision ranking for several generation portfolios (see section 7.4 on page 197):

   a) Portfolios featuring 100% of diesel or grid power have the largest decision space. Those portfolios can be viewed as optimal or worst solutions depending on the chosen risk perspective in both the off-grid Australian and Chilean mine. For instance, a decision-maker with a positive outlook on fuel prices and a negative outlook on mine-life would favour 100% fuel-based power systems over least-cost portfolios that include both renewable and fuel-based power - see figure 7.1 on page 201.

b) Portfolios featuring 100% of renewable power always remain at the bottom of the cost ranking independently of the chosen risk perspective - hence further demonstrating that fuel-based power is required to economically balance hybrid renewable power systems at times of low renewable resources.

c) Grid-connected portfolios have been found to be particularly sensitive to the mine-life risk factor. As a result, a pessimistic outlook on mine-life and a neutral outlook on other factors would favour grid power over other alternatives in the Chilean grid-connected mine.

d) Pessimistic risk factors for fuel and carbon prices in the off-grid Yukon mine both lead to an uptake of significant wind power so as to alleviate the cost risk associated with CCGT and diesel fuel prices.

7. Overall, RQ3 has further demonstrated that RQ1 results are robust solutions as they remain unchanged by most risk perspectives in the decision-analysis for the off-grid Chilean and Australian mines. On the contrary, the RQ1 optimal mix of the grid-connected Chilean mine and the off-grid Yukon mine are more fragile solutions that can be significantly altered by portfolio cost risks. More certainty on carbon policies from governing bodies would contribute to reducing the cost risk and therefore increase the attractiveness of renewable power generation in those mines (as argued in chapter 8 on page 213).

9.3 ORIGINALITY AND CONTRIBUTION

Based on the research problem and the relevant past studies associated with this PhD (discussed in chapters 1 on page 1 and 2 on page 17), the research contributions of this PhD fall in three major areas: 1) re-contextualisation of existing techniques, 2) combining two or more concepts and demonstrating evidence that the combination brings something useful, and 3) expansion of existing models (Petre and Rugg, 2010). In turn, the justification for each contribution is provided as follows[2].

[2]Note that research contributions are also discussed in section 2.5 on page 37 along with research gaps.

9.3.1 *Re-contextualisation of existing techniques to mining settings*

Whereas past studies provide a range of cost estimates and outcomes for hybrid renewable power systems, no authoritative peer-reviewed studies have characterised the economic potential of such systems for mining settings. At the same time, it was demonstrated in section 1.4 on page 13 that the mining industry is different to other industries on many levels and hence requires specific analyses that can accurately and meaningfully value the economic potential of hybrid renewable power systems for mining settings.

A re-contextualisation of existing methods have therefore been performed in this thesis with respect to a novel context: the mining industry. The model HELiOS-Mining was specifically developed in order to incorporate several modelling methods that are relevant for the research questions of this thesis. A meta-heuristic optimisation algorithm has been applied in HELiOS-Mining in order to determine the least-cost technological configurations in all selected mines (as detailed in section 3.3 on page 50). The optimisation was performed by utilising existing calculation methods for energy outputs, power dispatch, adequacy measurements, and economic metrics - as detailed in the methodology chapter 3 on page 45. In turn, the Markowitz portfolio theory was applied in chapter 7 on page 181 to assess the cost risk of a range of generation portfolios. Whereas previous studies have applied portfolio theory on large centralized power systems (Awerbuch and Berger, 2003; Jansen et al., 2006), this thesis presents a novel application of such approach that focuses on small-scale and off-grid settings. Further, it was demonstrated that the time-series associated with the mine-life risk do not follow a normal distribution. The semi-variance was subsequently introduced to tackle this methodological issue. The semi-variance has not been previously used in energy portfolios (as country-scale energy systems present little or no risk from an investment period perspective), and therefore constitutes another area of originality. Finally, the decision-analysis framework given by Arnold et al. (2002) was adopted in order to provide further insights on portfolio risk factors.

9.3.2 *Combination of portfolio theory and decision-analysis*

In chapter 7 on page 181, the disaggregated results of portfolio theory were used in a decision-analysis framework with respect to each risk factor. It was argued that a decision-maker might consider each portfolio risk factor independently in association with its attitude to risk and context-specific factors. For instance, a decision-maker with a positive outlook on fuel prices and a negative outlook on mine-life could favour portfolios that feature 100% of fuel-based power instead of least-cost portfolios that include both renewable and fuel-based power. By combining these two approaches, it was conclusively demonstrated that further useful insights can be generated for decision-making. As a result, the combination of the portfolio theory (Markowitz, 1952) and the MaxiMin/MaxiMax decision framework (Arnold et al., 2002) constitutes another area of research originality in this PhD thesis.

9.3.3 *Expansion of current models*

A number of modelling capabilities were required for this research, including: system simulation of islanded systems, renewable and storage integration (e.g. wind, solar, molten salt and battery storage), adequacy analysis, stochastic capabilities, cost optimisation, portfolio cost risk, and decision-making analysis. As shown in table D.1 on page 315, the full extent of these capabilities is not present in existing modelling tools. For instance, current models are not capable to combine cost risk (from a portfolio theory perspective), value of lost load, and stochastic modelling. Furthermore, existing models are not able to account for all of the selected technologies of this research (as detailed in 3.4.0.1 on page 51).

As a result, there was a need to expand on current research models in order to answer the research questions. Building on published methodologies of existing models (i.e. RenewIsland, RETScreen), a new energy optimisation model was developed in this PhD thesis. This state-of-the-art research tool, named HELiOS-Mining ("Hybrid Energy Load Optimisation System for the Mining industry"), is able to take into consideration the relevant methods, technologies, and parameters that were required to answer the research problem. This expansion of existing energy models constitutes the third contribution of this PhD thesis.

BIBLIOGRAPHY

Abbey, C., Robinson, J., Joos, G., 2008. Integrating renewable energy sources and storage into isolated diesel generator supplied electric power systems. IEEE, pp. 2178–2183. (Cited on pages 2 and 21.)

Abdelaziz, E. A., Saidur, R., Mekhilef, S., 2011. A review on energy saving strategies in industrial sector. Renewable and Sustainable Energy Reviews 15 (1), 150–168. (Cited on page 7.)

Ackermann, T., Andersson, G., Söder, L., 2001. Distributed generation: a definition. Electric power systems research 57 (3), 195–204. (Cited on page 12.)

Afgan, N. H., da Graca Carvalho, M., 2000. Energy system assessment with sustainability indicators. In: Sustainable Assessment Method for Energy Systems. Springer, pp. 83–125. (Cited on page 35.)

Aggarwal, S. K., Saini, L. M., Kumar, A., 2009. Electricity price forecasting in deregulated markets: A review and evaluation. International Journal of Electrical Power & Energy Systems 31 (1), 13–22. (Cited on page 185.)

Aguiar, R., Collares-Pereira, M., Conde, J., 1988. Simple procedure for generating sequences of daily radiation values using a library of Markov transition matrices. Solar Energy 40 (3), 269–279. (Cited on page 164.)

Ai, B., Yang, H., Shen, H., Liao, X., Aug. 2003. Computer-aided design of PV/wind hybrid system. Renewable Energy 28 (10), 1491–1512. (Cited on page 78.)

Albor Consuegra, F., Dimitrakopoulos, R., 2009. Stochastic mine design optimisation based on simulated annealing: pit limits, production schedules, multiple orebody scenarios and sensitivity analysis. Mining Technology 118 (2), 79–90. (Cited on pages 214 and 215.)

Allan, R., Billinton, R., 2000. Probabilistic assessment of power systems. Proceedings of the IEEE 88 (2), 140–162. (Cited on pages 11, 30, 31, 32, 33, and 67.)

Alvarado, S., Maldonado, P., Jaques, I., 1999. Energy and environmental implications of copper production. Energy 24 (4), 307–316. (Cited on page 7.)

Anderson, D., 2007. Electricity generation costs and investment, decisions: A review. Report. UKERC. (Cited on page 59.)

Arnold, B. F., Größl, I., Stahlecker, P., 2002. The minimax, the minimin, and the hurwicz adjustment principle. Theory and decision 52 (3), 233–260. (Cited on pages 34, 198, 237, and 238.)

Atwa, Y. M., El-Saadany, E. F., 2009. Reliability evaluation for distribution system with renewable distributed generation during islanded mode of operation. Power Systems, IEEE Transactions on 24 (2), 572–581. (Cited on page 29.)

Awerbuch, S., 2000. Investing in photovoltaics: risk, accounting and the value of new technology. Energy Policy 28 (14), 1023–1035. (Cited on pages 35, 36, and 133.)

Awerbuch, S., Berger, M., 2003. Applying portfolio theory to EU electricity planning and policy-making. IEA/EET working paper, 72. (Cited on pages 35, 36, 57, 70, and 237.)

Azapagic, A., 2004. Developing a framework for sustainable development indicators for the mining and minerals industry. Journal of cleaner production 12 (6), 639–662. (Cited on pages 2, 4, 5, 7, and 8.)

Balducci, P., Roop, J., Schienbein, L., DeSteese, J., Weimar, M., 2002. Electrical power interruption cost estimates for individual industries, sectors and US economy. Pacific Northwest National Laboratory. (Cited on pages xv, 30, 31, and 168.)

Banos, R., Manzano-Agugliaro, F., Montoya, F., Gil, C., Alcayde, A., Gómez, J., May 2011. Optimization methods applied to renewable and sustainable energy: A review. Renewable and Sustainable Energy Reviews 15 (4), 1753–1766. (Cited on pages 20 and 25.)

Bar-Lev, D., Katz, S., 1976. A portfolio approach to fossil fuel procurement in the electric utility industry. The Journal of Finance 31 (3), 933–947. (Cited on page 36.)

Barbour, A., 1994. Mining non-ferrous metals. Mining and its environmental impact. Edited by RE Hester and RM Harrison. Issues in Environmental Science and Technology, Royal Society of Chemistry, Letchworth, England, 1–15. (Cited on pages 5 and 6.)

Barton, J. P., Infield, D. G., 2004. Energy storage and its use with intermittent renewable energy. IEEE Transactions on Energy Conversion 19 (2), 441–448. (Cited on pages 21 and 37.)

Battisti, L., Baggio, P., Fedrizzi, R., 2006. Warm-air intermittent de-icing system for wind turbines. Wind Engineering 30 (5), 361–374. (Cited on page 97.)

Billinton, R., Allan, R. N., Allan, R. N., 1996. Reliability evaluation of power systems. Vol. 2. Springer Science. (Cited on pages 19, 66, 68, and 167.)

Billinton, R., Chowdhury, A., 1992. Incorporation of wind energy conversion systems in conventional generating capacity adequacy assessment. Vol. 139. IET, pp. 47–56. (Cited on page 28.)

Billinton, R., Karki, R., 1999a. Application of Monte Carlo simulation to generating system well-being analysis. Power Systems, IEEE Transactions on 14 (3), 1172–1177. (Cited on page 32.)

Billinton, R., Karki, R., 1999b. Capacity reserve assessment using system well-being analysis. Power Systems, IEEE Transactions on 14 (2), 433–438. (Cited on page 32.)

Billinton, R., Karki, R., 2001. Maintaining supply reliability of small isolated power systems using renewable energy. Vol. 148. IET, pp. 530–534. (Cited on page 29.)

Billinton, R., Wacker, G., Tollefson, G., 1993. Assessment of reliability worth in electric power systems in canada. Final Report for NSERC strategic grant STR0045005. (Cited on page 30.)

Blarke, M. B., 2008. The missing link in sustainable energy. (Cited on page 310.)

Blarke, M. B., Lund, H., 2008. The effectiveness of storage and relocation options in renewable energy systems. Renewable Energy 33 (7), 1499–1507. (Cited on pages 118 and 311.)

Bolinger, M. A., 2009. The value of renewable energy as a hedge against fuel price risk: Analytic contributions from economic and finance theory. Lawrence Berkeley National Laboratory. (Cited on page 133.)

Bovenberg, A., Goulder, L. H., 2002. Environmental taxation and regulation. Handbook of public economics 3, 1471–1545. (Cited on page 9.)

Boyle, G., 2004. Renewable energy. OXFORD university press. (Cited on page 33.)

Boyse, F., Causevic, A., Duwe, E., Orthofer, M., Cullinen, M. S., 2014. Implementing renewable for off-grid operations. (Cited on pages 76, 77, and 221.)

Branker, K., Pathak, M., Pearce, J., 2011. A review of solar photovoltaic levelized cost of electricity. Renewable and Sustainable Energy Reviews 15 (9), 4470–4482. (Cited on pages 2, 59, and 60.)

Breyer, C., Gerlach, A., 2013. Global overview on grid-parity. Progress in photovoltaics: research and applications 21 (1), 121–136. (Cited on pages 1 and 8.)

Bruckner, T., Groscurth, H.-M., Kümmel, R., 1997. Competition and synergy between energy technologies in municipal energy systems. Energy 22 (10), 1005–1014. (Cited on page 309.)

Bruckner, T., Morrison, R., Handley, C., Patterson, M., 2003. High-resolution modeling of energy-services supply systems using deeco: overview and application to policy development. Annals of Operations Research 121 (1-4), 151–180. (Cited on page 309.)

Calabrese, G., 1947. Generating reserve capacity determined by the probability method. American Institute of Electrical Engineers, Transactions of the 66 (1), 1439–1450. (Cited on page 20.)

Castillo, F. D., Dimitrakopoulos, R., 2014. Joint effect of commodity price and geological uncertainty over the life of mine and ultimate pit limit. Mining Technology 123 (4), 207–219. (Cited on pages 214 and 215.)

Celik, A. N., 2003. Techno-economic analysis of autonomous PV-wind hybrid energy systems using different sizing methods. Energy Conversion and Management 44 (12), 1951–1968. (Cited on pages 18 and 19.)

Chong, J., Phillips, G. M., 2012. Measuring risk for cost of capital: The downside beta approach. Journal of Corporate Treasury Management 4 (4). (Cited on page 194.)

Connolly, D., Lund, H., Mathiesen, B. V., Leahy, M., 2010. A review of computer tools for analysing the integration of renewable energy into various energy systems. Applied Energy 87 (4), 1059–1082. (Cited on page 307.)

Conrad, H., Thomas, H., Jeff, A., Gary, G., Scott, C., Graham, G., Mike, H., Jesse, D., 2013. Casion project: Form 43-101f1 technical report feasibility study. Tech. rep., Western Copper and Gold.
URL http://www.westerncopperandgold.com/ (Cited on pages 93 and 105.)

Da Silva, A. M. L., Manso, L. A. F., Sales, W. S., Resende, L. C., Aguiar, M. J., Matos, M. A., Lopes, J. A. P., Miranda, V., 2007. Application of Monte Carlo simulation to generating system well-being analysis considering renewable sources. European transactions on electrical power 17 (4), 387–400. (Cited on pages 29 and 32.)

Dalton, G., Lockington, D., Baldock, T., 2009. Case study feasibility analysis of renewable energy supply options for small to medium-sized tourist accommodations. Renewable Energy 34 (4), 1134–1144. (Cited on pages 17 and 37.)

Davenport, W. G. L., King, M., Schlesinger, M., Biswas, A. K., 2002. Extractive metallurgy of copper. Elsevier. (Cited on page 11.)

Davis, R., Franks, D. M., 2011. The costs of conflict with local communities in the extractive industry. In: Proceedings of the First International Seminar on Social Responsibility in Mining, Santiago, Chile. Vol. 30. (Cited on page 221.)

DEA, 2012 2012. Technology data for energy plants. Tech. rep., Danish Energy Authority, Copenhagen, Denmark.
URL Energinet.dk (Cited on pages 100, 105, and 223.)

Deane, J. P., Ó Gallachóir, B., McKeogh, E., 2010. Techno-economic review of existing and new pumped hydro energy storage plant. Renewable and Sustainable Energy Reviews 14 (4), 1293–1302. (Cited on page 13.)

Delarue, E., De Jonghe, C., Belmans, R., D'haeseleer, W., 2011. Applying portfolio theory to the electricity sector: Energy versus power. Energy Economics 33 (1), 12–23. (Cited on pages 36 and 70.)

Denholm, P., Ela, E., Kirby, B., Milligan, M., 2010. The role of energy storage with renewable electricity generation. (Cited on page 1.)

Denholm, P., Margolis, R. M., 2007. Evaluating the limits of solar photovoltaics (PV) in electric power systems utilizing energy storage and other enabling technologies. Energy Policy 35 (9), 4424–4433. (Cited on pages 34 and 118.)

Deshmukh, M., Deshmukh, S., 2008. Modeling of hybrid renewable energy systems. Renewable and Sustainable Energy Reviews 12 (1), 235–249. (Cited on page 82.)

Dowd, P., 1994. Risk assessment in reserve estimation and open-pit planning. Transactions of the Institution of Mining and Metallurgy(Section A: Mining Industry) 103. (Cited on page 215.)

Dufo-Lopez, R., Bernal-Agustin, J. L., 2008. Multi-objective design of pv, wind, diesel, hydrogen, battery systems. Renewable energy 33 (12), 2559–2572. (Cited on page 87.)

EASAC, 2011. Concentrating solar power: Its potential contribution to a sustainable energy future. EASAC Policy Report 16. (Cited on page 146.)

Edwards, J. L., Marnay, C., Bartholomew, E., Ouaglal, B., Siddiqui, A. S., LaCommare, K. S., 2002. Assessment of (mu) grid distributed energy resource potential using DER-CAM and GIS. (Cited on page 309.)

El-Shimy, M., 2009. Viability analysis of PV power plants in egypt. Renewable Energy 34 (10), 2187–2196. (Cited on page 312.)

EMR-Yukon, 2010. Energy for yukon: The natural gas option. Tech. rep., Oil and Gas.Yukon: Energy, Mines and Resources. (Cited on page 127.)

Emsley, J., 2011. Nature's building blocks: an AZ guide to the elements. Oxford University Press. (Cited on page 6.)

Engelhard, M., 2016. M+w group - expert opinion. (Cited on pages 49, 61, 65, 68, 73, 76, 87, 94, 100, 103, 104, 126, 129, 136, 143, and 168.)

Environment-Canada, 2003. Canadian wind energy atlas. (Cited on pages 95 and 167.)

Fiacco, A.-V., 1984. Introduction to sensitivity and stability analysis in nonlinear programming. (Cited on page 123.)

Firestone, R., 2004. Distributed energy resources customer adoption model technology data. Berkeley Lab, Berkeley, CA, USA Case Study. (Cited on page 309.)

Foody, P., 2014. A new approach to generate rins with biogas. (Cited on page 105.)

Georgilakis, P. S., Katsigiannis, Y. A., 2009. Reliability and economic evaluation of small autonomous power systems containing only renewable energy sources. Renewable Energy 34 (1), 65–70. (Cited on pages 27 and 29.)

Gerdes, K., Nichols, C., 2009. Water requirements for existing and emerging thermoelectric plant technologies. Rep. DOE/NETL-402 80108. (Cited on page 101.)

Giorsetto, P., Utsurogi, K. F., 1983. Development of a new procedure for reliability modeling of wind turbine generators. power apparatus and systems, ieee transactions on (1), 134–143. (Cited on page 28.)

Godfrey-Smith, P., 2006. The strategy of model-based science. Biology and Philosophy 21 (5), 725–740. (Cited on page 48.)

Goel, L., Gupta, R., 1997. A windows-based simulation tool for reliability evaluation of electricity generating capacity. International Journal of Engineering Education 13 (5), 347–357. (Cited on page 308.)

Grageda, M., Escudero, M., Alavia, W., Ushak, S., Fthenakis, V., 2016. Review and multi-criteria assessment of solar energy projects in chile. Renewable and Sustainable Energy Reviews 59, 583–596. (Cited on pages 129 and 190.)

Green, A., Diep, C., Dunn, R., Dent, J., 2015. High capacity factor CSP-PV hybrid systems. Energy Procedia 69, 2049–2059. (Cited on pages 96 and 120.)

Green, M. A., Emery, K., Hishikawa, Y., Warta, W., Dunlop, E. D., 2011. Solar cell efficiency tables (version 39). Progress in photovoltaics: research and applications 20 (1), 12–20. (Cited on page 99.)

Greening, L., Bataille, C., 2009. Bottom-up models of energy: across the spectrum. International Handbook on the Economics of Energy, 257–284. (Cited on page 306.)

Grubb, M., Edmonds, J., Ten Brink, P., Morrison, M., 1993. The costs of limiting fossil-fuel CO2 emissions: a survey and analysis. Annual Review of Energy and the environment 18 (1), 397–478. (Cited on pages xvii, 305, 306, and 307.)

Habib, M., Said, S., El-Hadidy, M., Al-Zaharna, I., 1999. Optimization procedure of a hybrid photovoltaic wind energy system. Energy 24 (11), 919–929. (Cited on page 83.)

Haralambopoulos, D., Polatidis, H., 2003. Renewable energy projects: structuring a multi-criteria group decision-making framework. Renewable Energy 28 (6), 961–973. (Cited on page 35.)

Harper, J., Karcher, M., Bolinger, M., 2007. Wind project financing structures: A review & comparative analysis. (Cited on page 220.)

Herrmann, U., Kelly, B., Price, H., Apr. 2004. Two-tank molten salt storage for parabolic trough solar power plants. SolarPACES 2002 29 (5–6), 883–893. (Cited on page 11.)

Hilson, G., Murck, B., Dec. 2000. Sustainable development in the mining industry: clarifying the corporate perspective. Resources Policy 26 (4), 227–238. (Cited on pages 2, 6, 7, and 8.)

Himri, Y., Boudghene Stambouli, A., Draoui, B., 2009. Prospects of wind farm development in algeria. Desalination 239 (1), 130–138. (Cited on page 312.)

Hinkley, J. T., Hayward, J. A., Curtin, B., Wonhas, A., Boyd, R., Grima, C., Tadros, A., Hall, R., Naicker, K., 2013. An analysis of the costs and opportunities for concentrating solar power in australia. Renewable Energy 57, 653–661. (Cited on pages 100, 104, and 146.)

Hogan, W. W., Warren, J. M., 1974. Toward the development of an equilibrium capital-market model based on semivariance. Journal of Financial and Quantitative Analysis 9 (01), 1–11. (Cited on page 194.)

Hu, E., Yang, Y., Nishimura, A., Yilmaz, F., Kouzani, A., 2010. Solar thermal aided power generation. Applied energy 87 (9), 2881–2885. (Cited on pages 11 and 225.)

Hu, P., Karki, R., Billinton, R., 2009. Reliability evaluation of generating systems containing wind power and energy storage. IET generation, transmission & distribution 3 (8), 783–791. (Cited on pages 29 and 32.)

Huneke, F., Henkel, J., González, J. A. B., Erdmann, G., 2012. Optimisation of hybrid off-grid energy systems by linear programming. Energy, Sustainability and Society 2 (1), 1–19. (Cited on pages 11, 18, 21, and 179.)

Ibrahim, H., Ghandour, M., Dimitrova, M., Ilinca, A., Perron, J., 2011. Integration of wind energy into electricity systems: Technical challenges and actual solutions. Energy Procedia 6 (0), 815–824. (Cited on page 2.)

IEA, 2012. Energy technology perspectives 2012: Pathways to a clean energy system. (Cited on page 143.)

Illingworth, V., 1991. The Penguin dictionary of physics. Penguin Books. (Cited on page 21.)

IPCC, 2011. Special report on renewable energy sources and climate change mitigation: Summary for policmakers and technical summary. Working Group III of the IPCC. (Cited on pages 12, 60, and 155.)

IRENA, 2012a. Renewable energy technologies: Cost analysis series biomass for power generation. (Cited on page 225.)

IRENA, 2012b. Renewable energy technologies: Cost analysis series for power generation: Concentrated solar power. (Cited on pages 145 and 146.)

Islegen, O., Reichelstein, S., 2011. Carbon capture by fossil fuel power plants: An economic analysis. Management Science 57 (1), 21–39. (Cited on page 59.)

Jackson, T., Green, K. P., 2015. Fraser institute annual survey of mining companies, 2014. Fraser Institute. (Cited on page 92.)

Jacoby, W. G., 2000. Loess:: a nonparametric, graphical tool for depicting relationships between variables. Electoral Studies 19 (4), 577–613. (Cited on page 117.)

Jansen, J., Beurskens, L., Van Tilburg, X., 2006. Application of portfolio analysis to the dutch generating mix. Energy research Center at the Netherlands (ECN) report C-05-100. (Cited on pages 35, 36, 69, 133, 147, 187, 188, 196, and 237.)

Jorgenson, J., Denholm, P., Mehos, M., Turchi, C., 2013. Estimating the performance and economic value of multiple concentrating solar power technologies in a production cost model. NREL. (Cited on pages 84, 85, and 174.)

Jotzo, F., 2012. Australia's carbon price. Nature Climate Change 2 (7), 475–476. (Cited on page 206.)

Kaldellis, J., Koronakis, P., Kavadias, K., 2004. Energy balance analysis of a stand-alone photovoltaic system, including variable system reliability impact. Renewable energy 29 (7), 1161–1180. (Cited on page 28.)

Kaldellis, J., Zafirakis, D., Kondili, E., 2009. Optimum autonomous stand-alone photovoltaic system design on the basis of energy pay-back analysis. Energy 34 (9), 1187–1198. (Cited on pages 18 and 24.)

Kalogirou, S. A., 2001. Use of TRNSYS for modelling and simulation of a hybrid pv–thermal solar system for cyprus. Renewable energy 23 (2), 247–260. (Cited on page 311.)

Kaltschmitt, M., Streicher, W., Wiese, A., 2007. Renewable energy: technology, economics and environment; 66 tables. Springer. (Cited on pages xv, 82, and 83.)

Karaki, S., Chedid, R., Ramadan, R., 1999. Probabilistic performance assessment of autonomous solar-wind energy conversion systems. Energy Conversion, IEEE Transactions on 14 (3), 766–772. (Cited on page 29.)

Karaki, S. H., Chedid, R. B., Ramadan, R., 2000. Probabilistic production costing of diesel-wind energy conversion systems. Energy Conversion, IEEE Transactions on 15 (3), 284–289. (Cited on page 28.)

Kariuki, K., Allan, R. N., 1996. Evaluation of reliability worth and value of lost load. IEE proceedings-Generation, transmission and distribution 143 (2), 171–180. (Cited on pages 27, 30, 31, and 68.)

Kashefi Kaviani, A., Riahy, G., Kouhsari, S., 2009. Optimal design of a reliable hydrogen-based stand-alone wind/PV generating system, considering component outages. Renewable energy 34 (11), 2380–2390. (Cited on pages 27, 29, and 163.)

Katiraei, F., Mauch, K., Dignard-Bailey, L., 2007. Integration of photovoltaic power systems in high-penetration clusters for distribution networks and mini-grids. International Journal of Distributed Energy Resources 3 (3), 207–224. (Cited on page 12.)

Kazempour, S. J., Moghaddam, M. P., Haghifam, M. R., Yousefi, G. R., 2009. Electric energy storage systems in a market-based economy: Comparison of emerging and traditional technologies. Renewable Energy 34 (12), 2630–2639. (Cited on pages 22 and 23.)

Kehlhofer, R., Rukes, B., Hannemann, F., Stirnimann, F., 2009. Combined-cycle gas & steam turbine power plants. Pennwell Books. (Cited on pages 88, 89, 95, 100, and 105.)

Khan, M., Iqbal, M., 2005. Pre-feasibility study of stand-alone hybrid energy systems for applications in newfoundland. Renewable energy 30 (6), 835–854. (Cited on page 310.)

Kimura, S., Sato, T., Kosugi, K., 2003. The effect of anti-icing paint on the adhension force of ice accretion on a wind turbine blade. BOREAS VI. FMI, Pyhätunturi, Finland, 9. (Cited on page 97.)

Kirby, J., 2014. Diavik diamond mine powers up with wind. (Cited on page 103.)

Kiureghian, A. D., Ditlevsen, O., 2009. Aleatory or epistemic? does it matter? Structural Safety 31 (2), 105–112. (Cited on page 33.)

KMPG, 2014. Taxes and incentives for renewable energy. (Cited on page 220.)

Kongnam, C., Nuchprayoon, S., Premrudeepreechacharn, S., Uatrongjit, S., 2009. Decision analysis on generation capacity of a wind park. Renewable and Sustainable Energy Reviews 13 (8), 2126–2133. (Cited on pages 23, 34, and 37.)

Korpaas, M., Holen, A. T., Hildrum, R., 2003. Operation and sizing of energy storage for wind power plants in a market system. International Journal of Electrical Power & Energy Systems 25 (8), 599–606. (Cited on pages 2, 18, 24, and 34.)

Kossoy, A., Peszko, G., Oppermann, K., Prytz, N., Klein, N., Blok, K., Lam, L., Wong, L., Borkent, B., 2015. State and trends of carbon pricing 2015. (Cited on page 216.)

Krajačić, G., Duić, N., Carvalho, M. d. G., 2009. H2 RES, energy planning tool for island energy systems–The case of the island of mljet. International journal of hydrogen energy 34 (16), 7015–7026. (Cited on page 310.)

Krajačić, G., Martins, R., Busuttil, A., Duić, N., da Graça Carvalho, M., 2008. Hydrogen as an energy vector in the islands' energy supply. International Journal of Hydrogen Energy 33 (4), 1091–1103. (Cited on page 310.)

Laffont, J. J., 1989. Economie de l'incertain et de l'information. MIT press. (Cited on page 33.)

Lagos, G., Mardones, F., 1999. Developing Domestic Resource Cost Approach to Identify the Economic and Environmental Impacts of Trade: the Mining Sector in Chile. (Cited on page 7.)

Laguna, M., 2011. Optquest: Optimization of complex systems. Opttek systems, INC. (Cited on page 50.)

Lahdelma, R., Salminen, P., Hokkanen, J., 2000. Using multicriteria methods in environmental planning and management. Environmental management 26 (6), 595–605. (Cited on page 34.)

Lawton, L., Sullivan, M., Van Liere, K., Katz, A., Eto, J., 2003. A framework and review of customer outage costs: Integration and analysis of electric utility outage cost surveys. (Cited on pages 30 and 67.)

Lazard, 2014. Lazard levelized cost of energy analysis version 8.0.
URL http://www.lazard.com/ (Cited on pages 103, 142, and 143.)

Lee, T. Y., Chen, C. L., 2009. Wind-photovoltaic capacity coordination for a time-of-use rate industrial user. Renewable Power Generation, IET 3 (2), 152–167. (Cited on pages 25 and 37.)

Lehmann, H., 2003. Energy-rich japan. Institute for Sustainable Solutions and Innovations. (Cited on page 312.)

Leng, G., Meloche, N., Monarque, A., Painchaud, G., Thevenard, D., Ross, M., Hosette, P., 2004. Clean energy project analysis: RETScreen, engineering & cases textbookphotovoltaic project analysis. CANMET Energy Technol. Center, Ottawa, ON, Canada. (Cited on page 312.)

Lerer, M., Duic, N., Alves, L. M., Carvalho, M. G., 2007. H 2 RES, energy planning tool for increasing the penetration of renewable energy sources in island energy supply. 2004 New and Renewable Energy Technologies for Sustainable Development, Evora, Portugal, 28 June-1 July 2004, 15. (Cited on page 310.)

Li, C.-H., Zhu, X.-J., Cao, G.-Y., Sui, S., Hu, M.-R., 2009. Dynamic modeling and sizing optimization of stand-alone photovoltaic power systems using hybrid energy storage technology. Renewable Energy 34 (3), 815–826. (Cited on page 24.)

Li, F., 2013. Spatially explicit techno-economic optimisation modellingof uk heating futures. Ph.D. thesis, UCL Energy Institute. (Cited on page 50.)

Li, G., Liu, C.-C., Lawarree, J., Gallanti, M., Venturini, A., 2005. State-of-the-art of electricity price forecasting. In: CIGRE/IEEE PES, 2005. International Symposium. IEEE, pp. 110–119. (Cited on page 186.)

Li, W., 2002. Incorporating aging failures in power system reliability evaluation. Power Systems, IEEE Transactions on 17 (3), 918–923. (Cited on pages 29 and 30.)

Li, W., Mansour, Y., Korczynski, J., Mills, B., 1995. Application of transmission reliability assessment in probabilistic planning of BC hydro vancouver south metro system. Power Systems, IEEE Transactions on 10 (2), 964–970. (Cited on page 29.)

Li, W., Zein, A., Kara, S., Herrmann, C., 2011. An investigation into fixed energy consumption of machine tools. In: Glocalized Solutions for Sustainability in Manufacturing. Springer, pp. 268–273. (Cited on page 73.)

Lilienthal, P., Gilman, P., Lambert, T., 2005. HOMER® Micropower Optimization Model. United States. Department of Energy. (Cited on page 310.)

Loomes, G., Sugden, R., 1982. Regret theory: An alternative theory of rational choice under uncertainty. The Economic Journal 92 (368), 805–824. (Cited on page 34.)

Luna-Rubio, R., Trejo-Perea, M., Vargas-Vázquez, D., Ríos-Moreno, G., 2012. Optimal sizing of renewable hybrids energy systems: A review of methodologies. Solar Energy 86 (4), 1077–1088. (Cited on pages 17, 19, and 20.)

Lund, H., Duić, N., Graça Carvalho, M. d., 2007. Two energy system analysis models: a comparison of methodologies and results. Energy 32 (6), 948–954. (Cited on page 308.)

Lund, H., Münster, E., 2003. Modelling of energy systems with a high percentage of CHP and wind power. Renewable Energy 28 (14), 2179–2193. (Cited on page 308.)

Lund, H., Salgi, G., Elmegaard, B., Andersen, A. N., 2009. Optimal operation strategies of compressed air energy storage (CAES) on electricity spot markets with fluctuating prices. Applied Thermal Engineering 29 (5), 799–806. (Cited on pages 24 and 309.)

Maghraby, H., Shwehdi, M., Al-Bassam, G. K., 2002. Probabilistic assessment of photovoltaic (PV) generation systems. Power Systems, IEEE Transactions on 17 (1), 205–208. (Cited on page 32.)

Mahon, L., 1992. Diesel generator handbook. Butterworth-Heinemann. (Cited on page 88.)

Maissan, J. F., 2013. Yukon energy wind workshop, wind development in yukon. URL http://www.yukonenergy.ca/ (Cited on page 99.)

Manfren, M., Caputo, P., Costa, G., 2011. Paradigm shift in urban energy systems through distributed generation: Methods and models. Applied Energy 88 (4), 1032–1048. (Cited on pages 307 and 308.)

Markowitz, H., 1952. Portfolio selection*. The journal of finance 7 (1), 77–91. (Cited on pages 35, 187, and 238.)

Marsh, W., 1979. Requirements assessment of wind power plants in electric utility systems. Vol. 1. pp. 110–124. (Cited on page 28.)

Mathiesen, B. V., 2008. Fuel cells and electrolysers in future energy systems. Videnbasen for Aalborg UniversitetVBN, Aalborg UniversitetAalborg University, Det Teknisk-Naturvidenskabelige FakultetThe Faculty of Engineering and Science, Det Danske Center for MiljøvurderingThe Danish Centre for Environmental Assessment. (Cited on page 308.)

Mayer, C., Ilinca, A., Fortin, G., Perron, J., et al., 2007. Wind tunnel study of electrothermal de-icing of wind turbine blades. International Journal of Offshore and Polar Engineering 17 (3), 182. (Cited on page 97.)

McCarthy, J., Monkhouse, P. H., 2002. To open or not to open, or what to do with a closed copper mine. Journal of Applied Corporate Finance 15 (2), 63–73. (Cited on page 216.)

McCrone, A., Finance, B. N. E., 2012. Global trends in renewable energy investment 2012. Frankfurt School of Finance and Management Frankfurt. (Cited on page 103.)

McLellan, B., Corder, G., Giurco, D., Ishihara, K., Sep. 2012. Renewable energy in the minerals industry: a review of global potential. Journal of Cleaner Production 32 (0), 32–44. (Cited on pages xii, xv, 1, 2, 4, 7, 9, 10, and 11.)

Melo, A., Pereira, M., 1995. Sensitivity analysis of reliability indices with respect to equipment failure and repair rates. Power Systems, IEEE Transactions on 10 (2), 1014–1021. (Cited on page 29.)

Mendelsohn, M., Kreycik, C., Bird, L., Schwabe, P., Cory, K., 2012. Impact of financial structure on the cost of solar energy. Contract 303, 275–3000. (Cited on pages 63, 64, and 219.)

Merton, R. C., et al., 1972. An analytic derivation of the efficient portfolio frontier. Journal of financial and quantitative analysis 7 (4), 1851–1872. (Cited on page 191.)

Middelberg, A., Zhang, J., Xia, X., 2009. An optimal control model for load shifting–with application in the energy management of a colliery. Applied Energy 86 (7), 1266–1273. (Cited on page 75.)

Mildenberger, M., Howe, P. D., Lachapelle, E., Stokes, L. C., Marlon, J. R., Gravelle, T., 2016. The distribution of climate change public opinion in canada. Available at SSRN 2732935. (Cited on page 206.)

Miller, D., Hope, C., 2000. Learning to lend for off-grid solar power: policy lessons from world bank loans to india, indonesia, and sri lanka. Energy Policy 28 (2), 87–105. (Cited on page 12.)

Ming, D., Yichun, W., 2006. Optimal expansion planning of wind-diesel energy system. IEEE, pp. 1–6. (Cited on page 28.)

Misak, S., Prokop, L., 2010. Off-grid power systems. IEEE, pp. 14–17. (Cited on page 12.)

Mohammad Rozali, N. E., Wan Alwi, S. R., Abdul Manan, Z., Klemeš, J. J., Hassan, M. Y., 2013. Process integration of hybrid power systems with energy losses considerations. Energy. (Cited on page 22.)

Moomaw, W., Burgherr, P., Heat, G., Lenzen, M., Nyboer, J., Verbgruggen, A., 2011. Annex II: Methodology. In IPCC Special Report on Renewable Energy Sources and Climate Change Mitigation. Cambridge (UK) and New York (USA), Cambridge University Press. (Cited on pages 59 and 62.)

Morales, Mocarquer, Rudnick, Miquel, 2015. Benefits of industrial demand response in the chilean electricity market. Systep. (Cited on page 137.)

Morrison, R., Bruckner, T., 2002. High-resolution modeling of distributed energy resources using deeco: adverse interactions and potential policy conflicts. pp. 24–28. (Cited on page 309.)

Najjar, Y. S., 2001. Efficient use of energy by utilizing gas turbine combined systems. Applied Thermal Engineering 21 (4), 407–438. (Cited on page 13.)

Nakata, T., 2004. Energy-economic models and the environment. Progress in Energy and Combustion Science 30 (4), 417–475. (Cited on pages xvii and 306.)

Nasdaq, 2016. End of day commodity futures price quotes for high grade copper. URL http://www.nasdaq.com/markets/copper.aspx (Cited on pages xii and 5.)

Nasirov, S., Silva, C., Agostini, C. A., 2015. Investors perspectives on barriers to the deployment of renewable energy sources in chile. Energies 8 (5), 3794–3814. (Cited on page 221.)

NCEP, 2010. Ncep climate forecast system reanalysis (cfsr) selected hourly time-series products, january 1979 to december 2010. Research Data Archive at the National Center for Atmospheric Research, Computational and Information Systems Laboratory, Boulder, CO.[Available online at http://rda. ucar. edu/datasets/ds093. 1.]. (Cited on pages 95 and 164.)

Nikolakakis, T., Fthenakis, V., 2011. The optimum mix of electricity from wind-and solar-sources in conventional power systems: Evaluating the case for new york state. Energy Policy 39 (11), 6972–6980. (Cited on page 120.)

Norgate, T., Haque, N., Feb. 2010. Energy and greenhouse gas impacts of mining and mineral processing operations. Journal of Cleaner Production 18 (3), 266–274. (Cited on pages 1, 7, 9, 10, and 11.)

Norgate, T., Jahanshahi, S., 2006. Energy and greenhouse gas implications of deteriorating quality ore reserves. (Cited on page 9.)

Norgate, T., Jahanshahi, S., 2010. Low grade ores–Smelt, leach or concentrate? Minerals Engineering 23 (2), 65–73. (Cited on pages 73 and 74.)

Nottrott, A., Kleissl, J., Washom, B., 2013. Energy dispatch schedule optimization and cost benefit analysis for grid-connected, photovoltaic-battery storage systems. Renewable Energy 55, 230–240. (Cited on page 21.)

Nrel, 2012. Cost and performance data for power generation technologies. (Cited on page 33.)

NREL, 2012 2012. Cost and performance data for power generation technologies. (Cited on page 103.)

NREL, 2015. Nrel annual technology baseline 2015. (Cited on page 142.)

Nykvist, B., Nilsson, M., 2015. Rapidly falling costs of battery packs for electric vehicles. Nature Climate Change 5 (4), 329–332. (Cited on pages 120, 140, and 141.)

Oanda, 2016. Yearly averages of historical exchange rates. URL www.oanda.com (Cited on page 184.)

OECD-Stats, 2014. Consumer prices (MEI).
URL http://stats.oecd.org/ (Cited on page 65.)

Paatero, J. V., Lund, P. D., 2006. A model for generating household electricity load profiles. International journal of energy research 30 (5), 273–290. (Cited on page 75.)

Paliwal, P., Patidar, N., Nema, R., Mar. 2014a. Determination of reliability constrained optimal resource mix for an autonomous hybrid power system using particle swarm optimization. Renewable Energy 63 (0), 194–204. (Cited on page 28.)

Paliwal, P., Patidar, N., Nema, R., 2014b. A novel method for reliability assessment of autonomous PV-wind-storage system using probabilistic storage model. International Journal of Electrical Power & Energy Systems 55, 692–703. (Cited on page 28.)

Pannell, D. J., 1997. Sensitivity analysis of normative economic models: theoretical framework and practical strategies. Agricultural economics 16 (2), 139–152. (Cited on pages 123 and 149.)

Papathanassiou, S. A., Boulaxis, N. G., 2006. Power limitations and energy yield evaluation for wind farms operating in island systems. Renewable energy 31 (4), 457–479. (Cited on page 29.)

Paraszczak, J., Fytas, K., 2012. Renewable energy sources–a promising opportunity for remote mine sites? In Proceedings of the International Conference on Renewable Energies and Power Quality 2012. (Cited on pages 2, 6, 8, and 12.)

Parent, O., Ilinca, A., 2011. Anti-icing and de-icing techniques for wind turbines: Critical review. Cold regions science and technology 65 (1), 88–96. (Cited on pages 97, 98, 99, and 142.)

Parrado, C., Girard, A., Simon, F., Fuentealba, E., 2016. 2050 LCoe (levelized cost of energy) projection for a hybrid PV (photovoltaic)-CSP (concentrated solar power) plant in the atacama desert, chile. Energy 94, 422–430. (Cited on page 129.)

Parry, I., Strand, J., 2012. International fuel tax assessment: an application to chile. Environment and Development Economics 17 (02), 127–144. (Cited on pages xiii and 184.)

Patel, M. R., 2005. Wind and solar power systems: design, analysis, and operation. CRC press. (Cited on page 82.)

Paulus, M., Borggrefe, F., 2011. The potential of demand-side management in energy-intensive industries for electricity markets in germany. Applied Energy 88 (2), 432–441. (Cited on page 75.)

Peltola, E., Laakso, T., Antikainen, P., Peuranen, S., 2003. Prevention of icing effects. BOREAS VI. FMI, Pyhätunturi, Finland, 9. (Cited on page 99.)

Peter, S., Lehmann, H., Puig, J., Garcia, M., 2009. Solar catalonia II, a pathway to a 100% renewable energy system for catalonia. Institute for Sustainable Solutions and Innovations, World Council for Renewable Energy, European Association for Renewable Energy, and Ecoserveis, Barcelona/Makkleeberg. (Cited on page 312.)

Petersen, S. R., 1993. Energy prices and discount factors for life-cycle cost analysis 1994. Supplement to National Institute of Standards and Technology Handbook 135. (Cited on page 65.)

Petre, M., Rugg, G., 2010. The unwritten rules of PhD research. McGraw-Hill International. (Cited on page 236.)

Philibert, C., 2010. Technology roadmap: concentrating solar power. OECD/IEA. (Cited on page 225.)

Pihl, E., 2009. Concentrating solar power. (Cited on page 11.)

Pinard, J.-P., 2007. Wind climate of the whitehorse area. Arctic, 227–237. (Cited on page 167.)

Pitt, C. H., Wadsworth, M. E., 1980. Assessment of energy requirements in proven and new copper processes. (Cited on page 74.)

Pohekar, S., Ramachandran, M., 2004. Application of multi-criteria decision making to sustainable energy planning—a review. Renewable and Sustainable Energy Reviews 8 (4), 365–381. (Cited on page 34.)

Protogeropoulos, C., Brinkworth, B., Marshall, R., 1997. Sizing and techno-economical optimization for hybrid solar photovoltaic/wind power systems with battery storage. International Journal of Energy Research 21 (6), 465–479. (Cited on page 19.)

Rabiee, A., Khorramdel, H., Aghaei, J., 2013. A review of energy storage systems in microgrids with wind turbines. Renewable and Sustainable Energy Reviews 18 (0), 316–326. (Cited on page 2.)

Rastler, D., 2010. Electricity energy storage technology options: a white paper primer on applications, costs and benefits. Electric Power Research Institute. (Cited on page 13.)

Rehman, S., El-Amin, I., 2015. Study of a solar pv/wind/diesel hybrid power system for a remotely located population near arar, saudi arabia. Energy Exploration & Exploitation 33 (4), 591–620. (Cited on page 96.)

Rehman, S., El-Amin, I., Ahmad, F., Shaahid, S., Al-Shehri, A., Bakhashwain, J., Shash, A., 2007. Feasibility study of hybrid retrofits to an isolated off-grid diesel power plant. Renewable and Sustainable Energy Reviews 11 (4), 635–653. (Cited on page 310.)

Remund, J., Kunz, S., Schilter, C., Müller, S., 2004. Meteonorm handbook. Bern: METOTEST. (Cited on pages 94, 164, and 165.)

Rigollier, C., Lefevre, M., Wald, L., 2004. The method heliosat-2 for deriving shortwave solar radiation from satellite images. Solar Energy 77 (2), 159–169. (Cited on page 164.)

Rivers, N., 2014. The Case for a Carbon Tax in Canada. Canada 2020. (Cited on page 155.)

Romero, H., 2008. Irradiancia solar en territorios de la república de chile. Valparaiso: Universidad Técnica Federico Santa María 248. (Cited on page 164.)

Roques, F. A., Newbery, D. M., Nuttall, W. J., 2008. Fuel mix diversification incentives in liberalized electricity markets: a mean–variance portfolio theory approach. Energy Economics 30 (4), 1831–1849. (Cited on page 36.)

Roy, A., Kedare, S. B., Bandyopadhyay, S., 2010. Optimum sizing of wind-battery systems incorporating resource uncertainty. Applied Energy 87 (8), 2712–2727. (Cited on page 28.)

Sebastian, R., 2009. Simulation of the transition from wind only mode to wind diesel mode in a no-storage wind diesel system. Latin America Transactions, IEEE (Revista IEEE America Latina) 7 (5), 539–544. (Cited on page 223.)

Seifert, H., 2003. Technical requirements for rotor blades operating in cold climate. BOREAS VI 9. (Cited on page 97.)

Shaahid, S., El-Amin, I., 2009. Techno-economic evaluation of off-grid hybrid photovoltaic–diesel–battery power systems for rural electrification in saudi Arabia—A way forward for sustainable development. Renewable and Sustainable Energy Reviews 13 (3), 625–633. (Cited on page 12.)

Shaahid, S., Elhadidy, M., 2007. Technical and economic assessment of grid-independent hybrid photovoltaic–diesel–battery power systems for commercial loads in desert environments. Renewable and sustainable energy reviews 11 (8), 1794–1810. (Cited on page 13.)

Shafiee, S., Topal, E., 2010. A long-term view of worldwide fossil fuel prices. Applied Energy 87 (3), 988 – 1000. (Cited on page 132.)

Shahin, A., Shirouyehzad, H., Pourjavad, E., 2012. Optimum maintenance strategy: a case study in the mining industry. International Journal of Services and Operations Management 12 (3), 368–386. (Cited on pages 72 and 73.)

Sharma, J., 2001. Quantitative Techniques for Managerial Decisions. Macmillan. (Cited on page 34.)

Sharp, E., Dodds, P., Barrett, M., Spataru, C., 2015. Evaluating the accuracy of cfsr reanalysis hourly wind speed forecasts for the uk, using in situ measurements and geographical information. Renewable Energy 77, 527–538. (Cited on page 166.)

Short, W., Packey, D. J., Holt, T., 2005. A manual for the economic evaluation of energy efficiency and renewable energy technologies. University Press of the Pacific. (Cited on pages 64, 65, 136, and 219.)

Siddiqui, A. S., Marnay, C., Edwards, J. L., Firestone, R., Ghosh, S., Stadler, M., 2005. Effects of carbon tax on microgrid combined heat and power adoption. Journal of Energy Engineering 131 (1), 2–25. (Cited on page 309.)

Singh, C., Lago-Gonzalez, A., 1985. Reliability modeling of generation systems including unconventional energy sources. Power Apparatus and Systems, IEEE Transactions on (5), 1049–1056. (Cited on page 28.)

Siskos, J., Hubert, P., 1983. Multi-criteria analysis of the impacts of energy alternatives: a survey and a new comparative approach. European Journal of Operational Research 13 (3), 278–299. (Cited on page 34.)

Slade, M. E., 2004. Competing models of firm profitability. International Journal of Industrial Organization 22 (3), 289–308. (Cited on page 6.)

Slavin, A., 2014. Cronimet 1mw PV hybrid – updated presentation | energy and mines. URL http://energyandmines.com/ (Cited on page 63.)

Sniedovich, M., 2010. Dynamic programming: Foundations and principles. CRC press. (Cited on page 23.)

SNL, 2016. Snl interactive. Online at http://www. snl. com, accessed November 2016. (Cited on page 92.)

Soni, A. K., Wolkersdorfer, C., 2016. Mine water: policy perspective for improving water management in the mining environment with respect to developing economies. International Journal of Mining, Reclamation and Environment 30 (2), 115–127. (Cited on page 117.)

Souliotis, M., Kalogirou, S., Tripanagnostopoulos, Y., 2009. Modelling of an ICS solar water heater using artificial neural networks and TRNSYS. Renewable Energy 34 (5), 1333–1339. (Cited on page 311.)

Stackhouse, P., Whitlock, C., 2008. Surface meteorology and solar energy (sse) release 6.0, nasa sse 6.0. Earth Science Enterprise Program, National Aeronautic and Space Administration (NASA), Langley, http://eosweb. larc. nasa. gov/sse. (Cited on pages 164 and 165.)

Starke, L., 2002. Breaking new ground: mining, minerals and sustainable development. London: Earthscan. (Cited on page 5.)

Streckiene, G., Andersen, A., Energiesysteme, I., 2010. Analysing the optimal size of a CHP unit and thermal store when a german CHP plant is selling at the spot market. Tech. rep., MASSIG EIE/07/164. (Cited on page 309.)

Tanrioven, M., Alam, M., 2006. Reliability modeling and analysis of stand-alone PEM fuel cell power plants. Renewable Energy 31 (7), 915–933. (Cited on page 28.)

TESLA, 2015. Tesla powerwall home battery.
URL http://www.teslamotors.com/powerwall (Cited on page 104.)

Tsung-Ying, L., 2007. Operating schedule of battery energy storage system in a time-of-use rate industrial user with wind turbine generators: A multipass iteration particle swarm optimization approach. Energy Conversion, IEEE Transactions on 22 (3), 774–782. (Cited on pages 24 and 26.)

Turchi, C., Mehos, M., Ho, C. K., Kolb, G. J., 2010. Current and future costs for parabolic trough and power tower systems in the us market. SolarPACES 2010. (Cited on pages 104, 144, and 145.)

TWP, 2015. Wind energy market intelligence database.
URL http://www.thewindpower.net/turbines_manufacturers_en.php (Cited on pages xvi and 98.)

Ulleberg, Ø., 1998. Stand-alone power systems for the future: optimal design, operation & control of solar-hydrogen energy systems. NTNU, Trondheim, Norvège. (Cited on page 311.)

Ulleberg, Ø., Nakken, T., Ete, A., 2010. The wind/hydrogen demonstration system at utsira in norway: Evaluation of system performance using operational data and updated hydrogen energy system modeling tools. International Journal of Hydrogen Energy 35 (5), 1841–1852. (Cited on page 311.)

UNIDO, 2010. Global industrial energy efficiency benchmarking. (Cited on pages 1 and 6.)

US-Dept-Energy, 2015. Clean Cities Alternative Fuel Price Report. US Department of Energy, Energy Efficiency and Renewable Energy, Clean Cities. (Cited on page 105.)

Ustun, T. S., Ozansoy, C., Zayegh, A., 2011. Recent developments in microgrids and example cases around the world—A review. Renewable and Sustainable Energy Reviews 15 (8), 4030–4041. (Cited on pages 12 and 37.)

Vallee, F., Lobry, J., Deblecker, O., 2008. System reliability assessment method for wind power integration. Power Systems, IEEE Transactions on 23 (3), 1288–1297. (Cited on page 28.)

Van Wyk, L., 2013. Diavik diamond mines inc. wind farm project. Energy and Mines. URL http://energyandmines.com/ (Cited on pages 98, 99, and 103.)

Victor, D., Zhou, D., others, 2014. Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Intergovernmental Panel on Climate Change, Geneva. http://www. ipcc. ch/report/ar5/wg3. (Cited on pages 59, 61, 103, 105, 141, and 143.)

Wacker, G., Billinton, R., 1989. Customer cost of electric service interruptions. Proceedings of the IEEE 77 (6), 919–930. (Cited on page 30.)

Wang, L., Singh, C., 2007. Environmental/economic power dispatch using a fuzzified multi-objective particle swarm optimization algorithm. Electric Power Systems Research 77 (12), 1654–1664. (Cited on page 25.)

Wang, L., Singh, C., 2008. Balancing risk and cost in fuzzy economic dispatch including wind power penetration based on particle swarm optimization. Electric Power Systems Research 78 (8), 1361–1368. (Cited on pages 25 and 34.)

Wang, P., Billinton, R., 2001. Time-sequential simulation technique for rural distribution system reliability cost/worth evaluation including wind generation as alternative supply. Vol. 148. IET, pp. 355–360. (Cited on page 29.)

Wang, X., Dai, H.-Z., Thomas, R., 1984. Reliability modeling of large wind farms and associateed electric utility interface systems. Power Apparatus and Systems, IEEE Transactions on (3), 569–575. (Cited on page 28.)

Wangdee, W., Billinton, R., 2006. Bulk electric system well-being analysis using sequential Monte Carlo simulation. Power Systems, IEEE Transactions on 21 (1), 188–193. (Cited on page 32.)

Watling, H., 2006. The bioleaching of sulphide minerals with emphasis on copper sulphides—a review. Hydrometallurgy 84 (1), 81–108. (Cited on page 7.)

Weisberg, M., 2007. Who is a modeler? The British journal for the philosophy of science 58 (2), 207–233. (Cited on page 48.)

Weisser, D., Garcia, R. S., 2005. Instantaneous wind energy penetration in isolated electricity grids: concepts and review. Renewable Energy 30 (8), 1299–1308, http://www.apmaths.uwo.ca/ mdavison/_library/natasha/windpenetrationRE.pdf. (Cited on page 1.)

Weitemeyer, S., Kleinhans, D., Vogt, T., Agert, C., 2015. Integration of renewable energy sources in future power systems: The role of storage. Renewable Energy 75, 14–20. (Cited on pages 118 and 119.)

Wen, J., Zheng, Y., Donghan, F., 2009. A review on reliability assessment for wind power. Renewable and Sustainable Energy Reviews 13 (9), 2485–2494. (Cited on page 28.)

Willis, K. G., Garrod, G. D., 1997. Electricity supply reliability: Estimating the value of lost load. Energy Policy 25 (1), 97–103. (Cited on page 31.)

Wilson, I. A. G., McGregor, P. G., Hall, P. J., 2010. Energy storage in the UK electrical network: Estimation of the scale and review of technology options. Energy Policy 38 (8), 4099–4106. (Cited on page 2.)

Wiser, R., 2014. 2014 wind technologies market report. (Cited on pages 122 and 141.)

Wiser, R., Lantz, E., Bolinger, M., Hand, M., 2012. Recent developments in the levelized cost of energy from us wind power projects. Presentation submitted to IEA Task 26. (Cited on page 141.)

Yang, H. X., Lu, L., Burnett, J., 2003. Weather data and probability analysis of hybrid photovoltaic–wind power generation systems in hong kong. Renewable Energy 28 (11), 1813–1824. (Cited on page 67.)

Yilmaz, P., Hakan Hocaoglu, M., Konukman, A. E. S., 2008. A pre-feasibility case study on integrated resource planning including renewables. Energy Policy 36 (3), 1223–1232. (Cited on pages 17 and 37.)

Yukon-Government, 2016. Yukon biomass energy strategy.
URL http://www.energy.gov.yk.ca/pdf/Yukon-Biomass-Energy-Strategy-Feb2016.pdf (Cited on page 225.)

Zhang, M., Middleton, R. H., Stone, P. M., Menabde, M., 2007. A reactive approach for mining project evaluation under price uncertainty. (Cited on pages 214 and 216.)

Zhang, Y., Smith, S. J., Kyle, G. P., Stackhouse Jr, P. W., 2010. Modeling the potential for thermal concentrating solar power technologies. Energy Policy 38 (12), 7884–7897. (Cited on pages 84 and 85.)

Zhou, P., Ang, B., Poh, K., 2006. Decision analysis in energy and environmental modeling: an update. Energy 31 (14), 2604–2622. (Cited on page 34.)

Zhu, L., Fan, Y., 2010. Optimization of china's generating portfolio and policy implications based on portfolio theory. Energy 35 (3), 1391–1402. (Cited on page 37.)

Zhu, Z., Graham, P., Reedman, L., Lo, T., 2009. A scenario-based integrated approach for modeling carbon price risk. Decisions in Economics and Finance 32 (1), 35–48. (Cited on pages 196 and 217.)

Zitzler, E., Thiele, L., Zitzler, E., Zitzler, E., Thiele, L., Thiele, L., 1998. An evolutionary algorithm for multiobjective optimization: The strength pareto approach. Citeseer. (Cited on page 25.)

Zoulias, E., Glockner, R., Lymberopoulos, N., Tsoutsos, T., Vosseler, I., Gavalda, O., Mydske, H., Taylor, P., 2006. Integration of hydrogen energy technologies in stand-alone power systems analysis of the current potential for applications. Renewable and sustainable energy reviews 10 (5), 432–462. (Cited on page 311.)

Zoulias, E. I., Lymberopoulos, N., 2007. Techno-economic analysis of the integration of hydrogen energy technologies in renewable energy-based stand-alone power systems. Renewable Energy 32 (4), 680–696. (Cited on page 22.)

Part V

APPENDIX

A

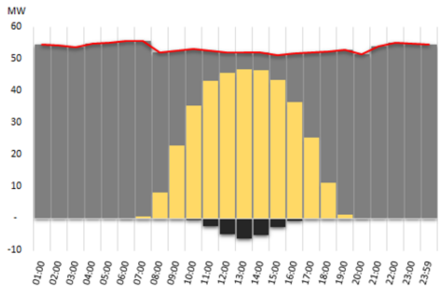
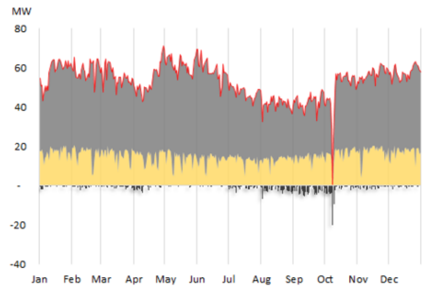
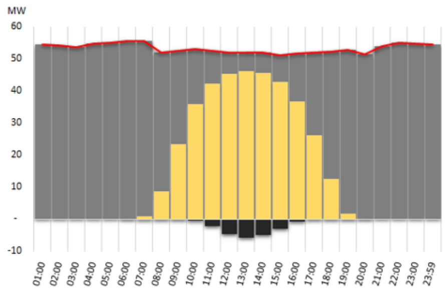
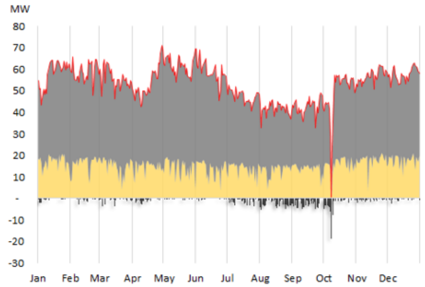
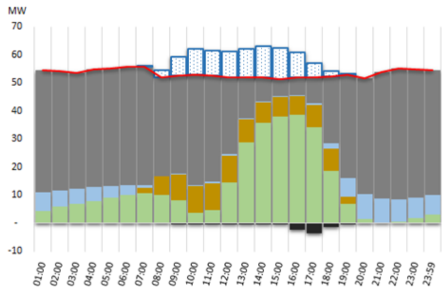
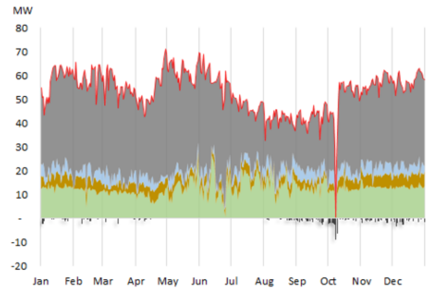
DETAILED MODELLING OUTPUTS

A.1 ATACAMA, CHILE (GRID-CONNECTED)

Table A.1: Detailed optimisation results: Atacama, Chile (Grid-Connected)

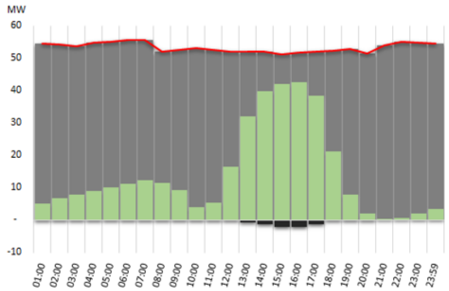
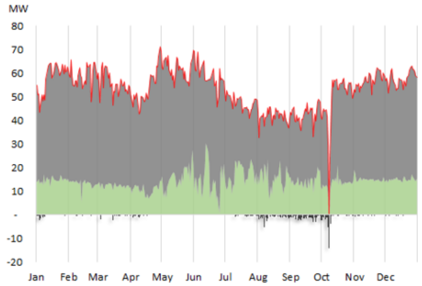
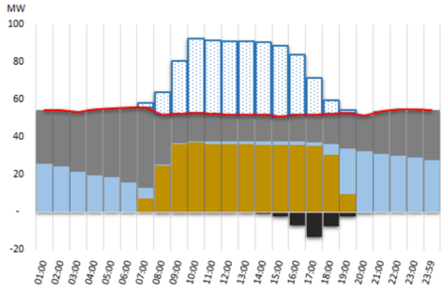
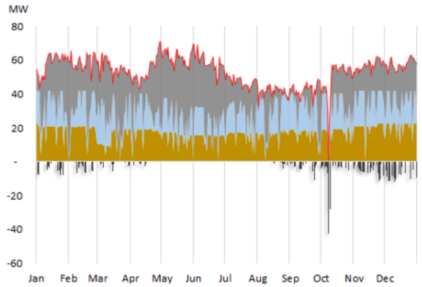
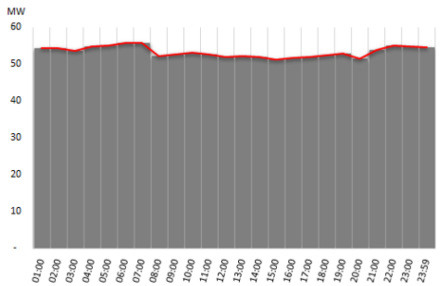
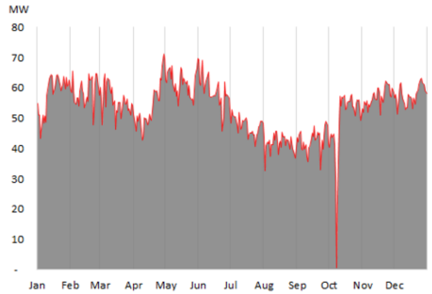
Rank		Technology	Size	Capacity Factor	% of Total Energy Supply	Total Output (yearly)	Total Curtailment (yearly)	Net LCOE	Gross LCOE	Capital Cost	TLCC	Life Cycle Direct Emissions ($KtCO_2eq$)	Land Use (Renewable Energy only)
1	**PV & Grid**	PV Tilted	66 MW	22%	27%	128 GWh	5.8 GWh	$0.103/kWh	$0.099/kWh	$109 M	$122 M		1.65 km²
		Grid	Existing grid connection		73%	340 GWh		$0.140/kWh			$439 M	7,310	
		Power System			**100%**	**468 GWh**	**5.8 GWh**	**$0.130/kWh**		**$109 M**	**$561 M**	**7,310**	**1.65 km²**
		Reliability	*100%*	*Renewable Energy*	*27%*								
		Hours of Storage (avg. dmd)	*0.0*	*Self-generation*	*27%*								
2	**PV Tracking & Grid**	PV 1-Axis tracking	62 MW	23%	27%	127 GWh	5.1 GWh	$0.108/kWh	$0.104/kWh	$113 M	$126 M		1.55 km²
		Grid	Existing grid connection		73%	341 GWh		$0.140/kWh			$441 M	7,339	
		Power System			**100%**	**468 GWh**	**5.1 GWh**	**$0.131/kWh**		**$113 M**	**$567 M**	**7,339**	**1.55 km²**
		Reliability	*100%*	*Renewable Energy*	*27%*								
		Hours of Storage (avg. dmd)	*0.0*	*Self-generation*	*27%*								
3	**Wind & CSP Tower & Grid**	Wind	52 MW	24%	24%	111 GWh	1.4 GWh	$0.117/kWh	$0.115/kWh	$99 M	$120 M		5.2 km²
		CSP Tower	27 MW										
		CSP Power Block	11 MW	67%	14%	65 GWh	3.2 GWh	$0.137/kWh		$71 M	$82 M	0	0.81 km²
		Thermal Storage	136 MWh										
		Grid	Existing grid connection		62%	292 GWh		$0.140/kWh			$377 M	6,282	
		Power System			**100%**	**468 GWh**	**4.6 GWh**	**$0.134/kWh**		**$169 M**	**$579 M**	**6,282**	**6.01 km²**
		Reliability	*100%*	*Renewable Energy*	*38%*	*CSP Net Eff.*	*14.2%*						
		Hours of Storage (avg. dmd)	*2.5*	*Self-generation*	*38%*	*CSP Backup*	*0.0%*						
4	**Wind & Grid**	Wind	59 MW	24%	27%	125 GWh	3.2 GWh	$0.118/kWh	$0.115/kWh	$112 M	$136 M		5.9 km²
		Grid	Existing grid connection		73%	343 GWh		$0.140/kWh			$443 M	7,388	
		Power System			**100%**	**468 GWh**	**3.2 GWh**	**$0.134/kWh**		**$112 M**	**$580 M**	**7,388**	**5.9 km²**
		Reliability	*100%*	*Renewable Energy*	*27%*								
		Hours of Storage (avg. dmd)	*0.0*	*Self-generation*	*27%*								
5	**CSP Tower & Grid**	CSP Tower	110 MW										
		CSP Power Block	42 MW	72%	57%	264 GWh	13.0 GWh	$0.133/kWh		$281 M	$326 M	0	3.3 km²
		Thermal Storage	523 MWh										
		Grid	Existing grid connection		43%	204 GWh		$0.140/kWh			$263 M	4,381	
		Power System			**100%**	**468 GWh**	**13.0 GWh**	**$0.136/kWh**		**$281 M**	**$589 M**	**4,381**	**3.3 km²**
		Reliability	*100%*	*Renewable Energy*	*57%*	*CSP Net Eff.*	*14.2%*						
		Hours of Storage (avg. dmd)	*12.5*	*Self-generation*	*57%*	*CSP Backup*	*0.0%*						
6	**Grid only**	Grid	Existing grid connection		100%	468 GWh		$0.140/kWh			$605 M	10,072	
		Power System			**100%**	**468 GWh**	**0.0 GWh**	**$0.140/kWh**		**$0 M**	**$605 M**	**10,072**	**0 km²**
		Reliability	*100%*	*Renewable Energy*	*0%*								
		Hours of Storage (avg. dmd)	*0.0*	*Self-generation*	*0%*								

Figure A.1: Power dispatch of optimal technological mixes (1/2): Atacama, Chile (Grid-Connected)

Rank	System type	Daily dispatch	Yearly dispatch
1	PV & Grid		
2	PV Tracking & Grid		
3	Wind & CSP Tower & Grid		

Wind | Solar PV | CSP | Storage Output | CSP Gas-backup | Grid | Gas Plant | Diesel Plant | Storage Gross Input | Spillages | Power Demand

Figure A.2: Power dispatch of optimal technological mixes (2/2): Atacama, Chile (Grid-Connected)

Rank	System type	Daily dispatch	Yearly dispatch
4	Wind & Grid		
5	CSP Tower & Grid		
6	Grid Only		

Wind · Solar PV · CSP · Storage Output · CSP Gas-backup · Grid · Gas Plant · Diesel Plant · Storage Gross Input · Spillages · Power Demand

A.2 ATACAMA, CHILE (OFF-GRID)

Table A.2: Detailed optimisation results (1/3): Atacama, Chile (Off-Grid)

Rank		Technology	Size	Capacity Factor	% of Total Energy Supply	Total Output (yearly)	Total Curtailment (yearly)	Net LCOE	Gross LCOE	Capital Cost	TLCC	Life Cycle Direct Emissions (KtCO$_2$eq)	Land Use (Renewable Energy only)
1	Wind & PV & CSP Tower (Gas backup) & Diesel	Wind	11 MW	25%	5%	24 GWh	0.2 GWh	$0.116/kWh	$0.115/kWh	$21 M	$25 M		1.1 km²
		PV Tilted	40 MW	23%	17%	81 GWh	0.6 GWh	$0.100/kWh	$0.099/kWh	$66 M	$74 M		1 km²
		CSP Tower	121 MW										
		CSP Power Block	60 MW	67%	75%	352 GWh	36.1 GWh	$0.169/kWh		$343 M	$550 M	1398	3.63 km²
		Thermal Storage	738 MWh										
		Diesel (rated)	45 MW	3%	2%	11 GWh		$0.696/kWh		$47 M	$71 M	209	
		Diesel (de-rated)	38 MW										
		Power System			**100%**	**468 GWh**	**36.9 GWh**	**$0.167/kWh**		**$478 M**	**$721 M**	**1,607**	**5.73 km²**
		Reliability (EIR)	*100.00%*	*Renewable Energy*	*80%*	*CSP Net Eff.*	*13.1%*						
		Hours of Storage (avg. dmd)	*13.8*	*Self-generation*	*100%*	*CSP Backup*	*17.9%*						
2	Wind & PV & CSP Tower & Diesel	Wind	33 MW	24%	15%	70 GWh	1.9 GWh	$0.119/kWh	$0.115/kWh	$63 M	$76 M		3.3 km²
		PV Tilted	33 MW	23%	14%	65 GWh	1.8 GWh	$0.102/kWh	$0.099/kWh	$54 M	$61 M		0.825 km²
		CSP Tower	122 MW										
		CSP Power Block	52 MW	55%	54%	253 GWh	54.8 GWh	$0.165/kWh		$333 M	$386 M	0	3.66 km²
		Thermal Storage	735 MWh										
		Diesel (rated)	85 MW	13%	17%	80 GWh		$0.375/kWh		$89 M	$278 M	1,507	
		Diesel (de-rated)	72 MW										
		Power System			**100%**	**468 GWh**	**58.5 GWh**	**$0.185/kWh**		**$539 M**	**$802 M**	**1,507**	**7.785 km²**
		Reliability (EIR)	*100.00%*	*Renewable Energy*	*83%*	*CSP Net Eff.*	*12.2%*						
		Hours of Storage (avg. dmd)	*13.8*	*Self-generation*	*100%*	*CSP Backup*	*0.0%*						
3	Wind & PV & CSP Tower (Gas backup) *No Diesel*	Wind	21 MW	24%	9%	44 GWh	1.8 GWh	$0.120/kWh	$0.115/kWh	$40 M	$48 M		2.1 km²
		PV Tilted	50 MW	22%	21%	97 GWh	4.1 GWh	$0.103/kWh	$0.099/kWh	$83 M	$93 M		1.25 km²
		CSP Tower	109 MW										
		CSP Power Block	127 MW	29%	70%	327 GWh	24.3 GWh	$0.215/kWh		$421 M	$676 M	1601	3.27 km²
		Thermal Storage	729 MWh										
		Power System			**100%**	**468 GWh**	**30.3 GWh**	**$0.185/kWh**		**$543 M**	**$821 M**	**1,601**	**6.62 km²**
		Reliability (EIR)	*99.96%*	*Renewable Energy*	*79%*	*CSP Net Eff.*	*12.5%*						
		Hours of Storage (avg. dmd)	*13.6*	*Self-generation*	*100%*	*CSP Backup*	*20.5%*						
4	CSP Tower & Diesel	CSP Tower	187 MW										
		CSP Power Block	60 MW	74%	83%	388 GWh	83.8 GWh	$0.153/kWh		$473 M	$549 M	0	5.61 km²
		Thermal Storage	1031 MWh										
		Diesel (rated)	88 MW	12%	17%	80 GWh		$0.381/kWh		$93 M	$280 M	1,494	
		Diesel (de-rated)	75 MW										
		Power System			**100%**	**468 GWh**	**83.8 GWh**	**$0.192/kWh**		**$566 M**	**$829 M**	**1,494**	**5.61 km²**
		Reliability (EIR)	*100.00%*	*Renewable Energy*	*83%*	*CSP Net Eff.*	*12.3%*						
		Hours of Storage (avg. dmd)	*19.3*	*Self-generation*	*100%*	*CSP Backup*	*0.0%*						
5	CSP Parabolic Trough (Gas backup) & Diesel	CSP Parabolic troughs	160 MW										
		CSP Power Block	59 MW	88%	97%	454 GWh	14.4 GWh	$0.196/kWh		$455 M	$822 M	2705	4.8 km²
		Thermal Storage	584 MWh										
		Diesel (rated)	40 MW	5%	3%	14 GWh		$0.575/kWh		$42 M	$73 M	257	
		Diesel (de-rated)	34 MW										
		Power System			**100%**	**468 GWh**	**14.4 GWh**	**$0.207/kWh**		**$497 M**	**$895 M**	**2,962**	**4.8 km²**
		Reliability (EIR)	*100%*	*Renewable Energy*	*62%*	*CSP Net Eff.*	*18.2%*						
		Hours of Storage (avg. dmd)	*10.9*	*Self-generation*	*100%*	*CSP Backup*	*34.7%*						

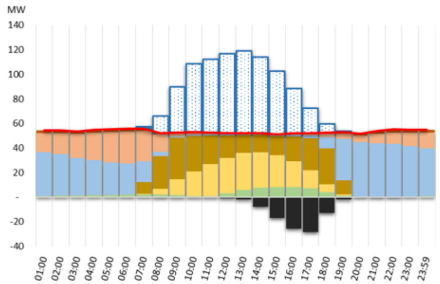
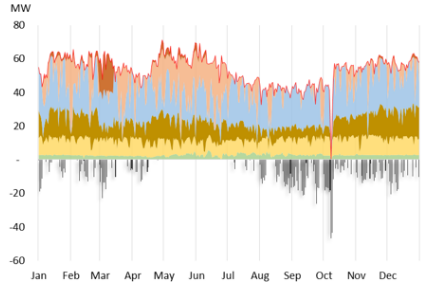
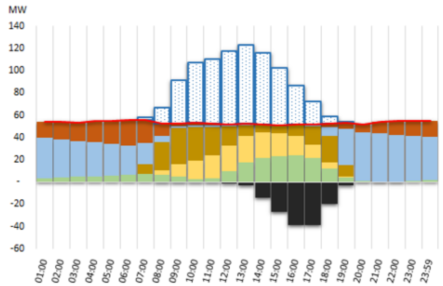
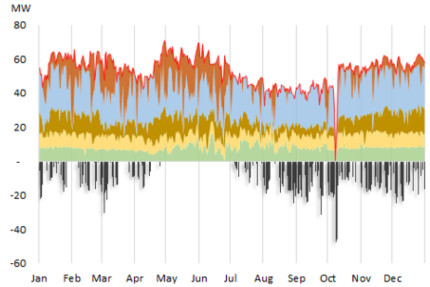
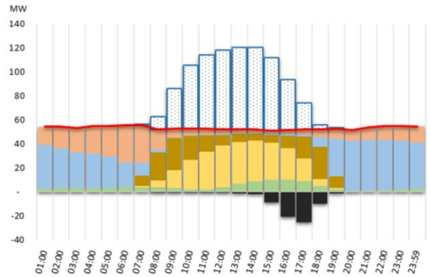
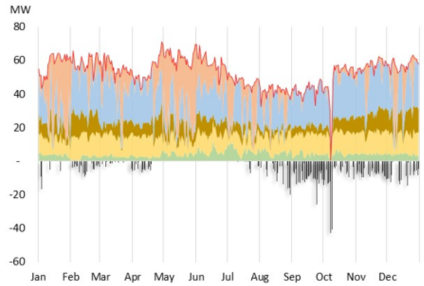
Table A.3: Detailed optimisation results (2/3): Atacama, Chile (Off-Grid)

Rank		Technology	Size	Capacity Factor	% of Total Energy Supply	Total Output (yearly)	Total Curtailment (yearly)	Net LCOE	Gross LCOE	Capital Cost	TLCC	Life Cycle Direct Emissions ($KtCO_2eq$)	Land Use (Renewable Energy only)
6	Wind & PV & CSP Parabolic Trough & Diesel	Wind	32 MW	23%	14%	65 GWh	4.1 GWh	$0.123/kWh	$0.115/kWh	$61 M	$74 M		3.2 km²
		PV Tilted	45 MW	22%	18%	86 GWh	5.4 GWh	$0.105/kWh	$0.099/kWh	$74 M	$83 M		1.125 km²
		CSP Parabolic troughs	113 MW	54%	41%	191 GWh	23.8 GWh	$0.228/kWh		$347 M	$402 M	0	3.39 km²
		CSP Power Block	40 MW										
		Thermal Storage	569 MWh										
		Diesel (rated)	85 MW	20%	27%	126 GWh		$0.335/kWh		$90 M	$389 M	2,365	
		Diesel (de-rated)	72 MW										
		Power System			**100%**	**468 GWh**	**33.3 GWh**	**$0.220/kWh**		**$572 M**	**$949 M**	**2,365**	**7.715 km²**
		Reliability (EIR)	*100%*	*Renewable Energy*	*73%*	*CSP Net Eff.*	*16.8%*						
		Hours of Storage (avg. dmd)	*10.7*	*Self-generation*	*100%*	*CSP Backup*	*0.0%*						
7	PV & CSP Parabolic Trough & Diesel	PV Tilted	69 MW	22%	28%	132 GWh	7.8 GWh	$0.105/kWh	$0.099/kWh	$114 M	$128 M		1.725 km²
		CSP Parabolic troughs	117 MW	56%	43%	200 GWh	22.2 GWh	$0.227/kWh		$362 M	$420 M	0	3.51 km²
		CSP Power Block	41 MW										
		Thermal Storage	609 MWh										
		Diesel (rated)	88 MW	21%	29%	136 GWh		$0.331/kWh		$93 M	$416 M	2,549	
		Diesel (de-rated)	75 MW										
		Power System			**100%**	**468 GWh**	**30.0 GWh**	**$0.223/kWh**		**$568 M**	**$963 M**	**2,549**	**5.235 km²**
		Reliability (EIR)	*100%*	*Renewable Energy*	*71%*	*CSP Net Eff.*	*17.0%*						
		Hours of Storage (avg. dmd)	*11.4*	*Self-generation*	*100%*	*CSP Backup*	*0.0%*						
8	Wind & PV & Battery & Diesel	Wind	54 MW	22%	19%	105 GWh	12.4 GWh	$0.129/kWh	$0.115/kWh	$103 M	$125 M		5.4 km²
		PV Tilted	69 MW	21%	23%	125 GWh	14.9 GWh	$0.111/kWh	$0.099/kWh	$114 M	$128 M		1.725 km²
		Battery Power	25 MW	14%	7%	30 GWh		$0.365/kWh		$52 M	$66 M		
		Battery Storage	136 MWh										
		Diesel (rated)	85 MW	38%	51%	241 GWh		$0.300/kWh		$90 M	$667 M	4,518	
		Diesel (de-rated)	73 MW										
		Power System			**100%**	**501 GWh**	**27.3 GWh**	**$0.230/kWh**		**$362 M**	**$988 M**	**3,072**	**7.125 km²**
		Reliability (EIR)	*100%*	*Renewable Energy*	*52%*								
		Hours of Storage (avg. dmd)	*2.5*	*Self-generation*	*100%*								
9	Wind & PV & Diesel	Wind	51 MW	20%	19%	87 GWh	23.7 GWh	$0.147/kWh	$0.115/kWh	$97 M	$118 M		5.1 km²
		PV Tilted	66 MW	18%	23%	105 GWh	28.8 GWh	$0.126/kWh	$0.099/kWh	$109 M	$122 M		1.65 km²
		Diesel (rated)	86 MW	43%	59%	276 GWh		$0.295/kWh		$90 M	$752 M	5,171	
		Diesel (de-rated)	73 MW										
		Power System			**100%**	**468 GWh**	**52.5 GWh**	**$0.232/kWh**		**$296 M**	**$992 M**	**5,171**	**6.75 km²**
		Reliability (EIR)	*100%*	*Renewable Energy*	*41%*								
		Hours of Storage (avg. dmd)	*0.0*	*Self-generation*	*100%*								
10	PV & Diesel	PV Tilted	84 MW	20%	32%	149 GWh	21.6 GWh	$0.113/kWh	$0.099/kWh	$139 M	$156 M		2.1 km²
		Diesel (rated)	89 MW	48%	68%	319 GWh		$0.292/kWh		$94 M	$859 M	5,979	
		Diesel (de-rated)	76 MW										
		Power System			**100%**	**468 GWh**	**21.6 GWh**	**$0.236/kWh**		**$232 M**	**$1,015 M**	**5,979**	**2.1 km²**
		Reliability (EIR)	*100%*	*Renewable Energy*	*32%*								
		Hours of Storage (avg. dmd)	*0.0*	*Self-generation*	*100%*								
11	CSP Parabolic Trough & Diesel	CSP Parabolic troughs	187 MW	69%	71%	330 GWh	27.7 GWh	$0.197/kWh		$519 M	$602 M	0	5.61 km²
		CSP Power Block	55 MW										
		Thermal Storage	728 MWh										
		Diesel (rated)	88 MW	21%	29%	138 GWh		$0.330/kWh		$93 M	$420 M	2,582	
		Diesel (de-rated)	75 MW										
		Power System			**100%**	**468 GWh**	**27.7 GWh**	**$0.236/kWh**		**$612 M**	**$1,022 M**	**2,582**	**5.61 km²**
		Reliability (EIR)	*100%*	*Renewable Energy*	*71%*	*CSP Net Eff.*	*17.6%*						
		Hours of Storage (avg. dmd)	*13.6*	*Self-generation*	*100%*	*CSP Backup*	*0.0%*						

Table A.4: Detailed optimisation results (3/3): Atacama, Chile (Off-Grid)

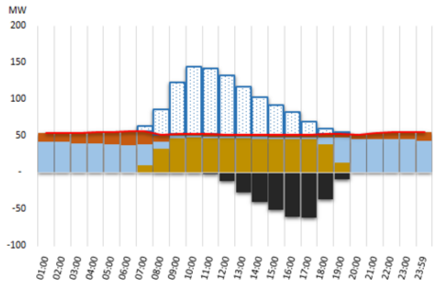
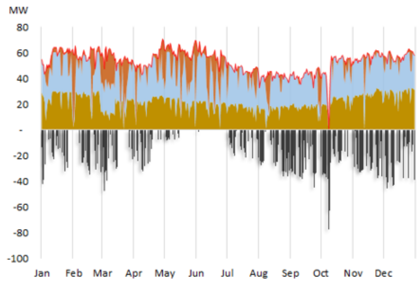
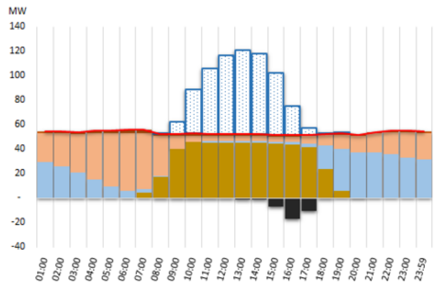
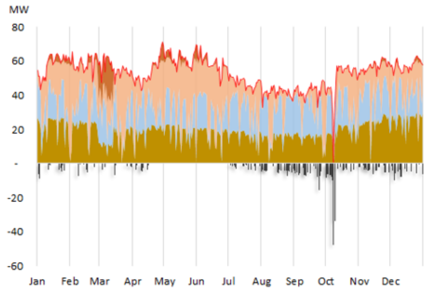
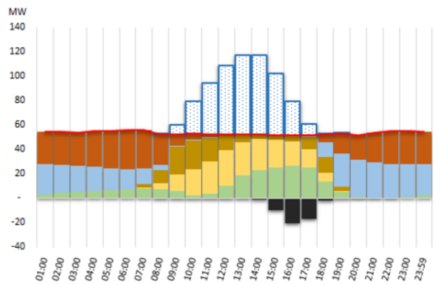
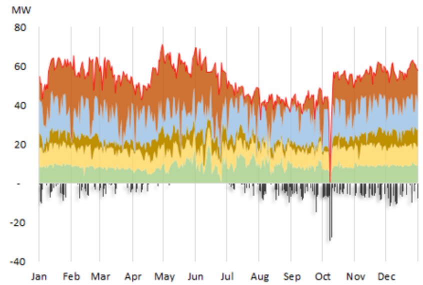
Rank		Technology	Size	Capacity Factor	% of Total Energy Supply	Total Output (yearly)	Total Curtailment (yearly)	Net LCOE	Gross LCOE	Capital Cost	TLCC	Life Cycle Direct Emissions ($KtCO_2eq$)	Land Use (Renewable Energy only)
12	PV Tracking & Diesel	PV 1-Axis tracking	81 MW	21%	32%	151 GWh	21.6 GWh	$0.119/kWh	$0.104/kWh	$147 M	$165 M		2.025 km²
		Diesel (rated)	89 MW	48%	68%	317 GWh		$0.292/kWh		$94 M	$855 M	5,944	
		Diesel (de-rated)	76 MW										
		Power System			**100%**	**468 GWh**	**21.6 GWh**	**$0.237/kWh**		**$241 M**	**$1,020 M**	**5,944**	**2.025 km²**
		Reliability (EIR)	*100%*	*Renewable Energy*	*32%*								
		Hours of Storage (avg. dmd)	*0.0*	*Self-generation*	*100%*								
13	PV & Battery & Diesel	PV Tilted	135 MW	21%	38%	248 GWh	26.7 GWh	$0.109/kWh	$0.099/kWh	$223 M	$250 M		3.375 km²
		Battery Power	45 MW	17%	14%	66 GWh		$0.348/kWh		$109 M	$138 M		
		Battery Storage	290 MWh										
		Diesel (rated)	89 MW	34%	48%	227 GWh		$0.304/kWh		$94 M	$636 M	4,251	
		Diesel (de-rated)	76 MW										
		Power System			**100%**	**540 GWh**	**26.7 GWh**	**$0.238/kWh**		**$426 M**	**$1,024 M**	**4,251**	**3.375 km²**
		Reliability (EIR)	*100%*	*Renewable Energy*	*58%*								
		Hours of Storage (avg. dmd)	*5.4*	*Self-generation*	*100%*								
14	Wind & Diesel	Wind	76 MW	22%	32%	149 GWh	15.8 GWh	$0.128/kWh	$0.115/kWh	$144 M	$175 M		7.6 km²
		Diesel (rated)	87 MW	49%	68%	319 GWh		$0.291/kWh		$92 M	$858 M	5,982	
		Diesel (de-rated)	74 MW										
		Power System			**100%**	**468 GWh**	**15.8 GWh**	**$0.240/kWh**		**$237 M**	**$1,034 M**	**5,982**	**7.6 km²**
		Reliability (EIR)	*100%*	*Renewable Energy*	*32%*								
		Hours of Storage (avg. dmd)	*0.0*	*Self-generation*	*100%*								
15	Diesel only	Diesel (rated)	89 MW	71%	100%	468 GWh		$0.283/kWh		$94 M	$1,220 M	8,773	
		Diesel (de-rated)	76 MW										
		Power System			**100%**	**468 GWh**	**0.0 GWh**	**$0.283/kWh**		**$94 M**	**$1,220 M**	**8,773**	**0 km²**
		Reliability (EIR)	*100%*	*Renewable Energy*	*0%*								
		Hours of Storage (avg. dmd)	*0.0*	*Self-generation*	*100%*								
16	Wind & PV & Battery	Wind	151 MW	13%	20%	169 GWh	158.1 GWh	$0.223/kWh	$0.115/kWh	$287 M	$349 M		15.1 km²
		PV Tilted	300 MW	12%	37%	315 GWh	294.4 GWh	$0.191/kWh	$0.099/kWh	$495 M	$556 M		7.5 km²
		Battery Power	93 MW	24%	43%	199 GWh		$0.494/kWh		$396 M	$499 M		
		Battery Storage	1089 MWh										
		Power System			**100%**	**683 GWh**	**452.4 GWh**	**$0.358/kWh**		**$1,178 M**	**$1,403 M**	**0**	**22.6 km²**
		Reliability (EIR)	*99%*	*Renewable Energy*	*100%*								
		Hours of Storage (avg. dmd)	*20.4*	*Self-generation*	*100%*								
17	PV & Battery	PV Tilted	396 MW	14%	44%	489 GWh	315.1 GWh	$0.162/kWh	$0.099/kWh	$653 M	$734 M		9.9 km²
		Battery Power	156 MW	19%	56%	260 GWh		$0.512/kWh		$636 M	$802 M		
		Battery Storage	1747 MWh										
		Power System			**100%**	**750 GWh**	**315.1 GWh**	**$0.382/kWh**		**$1,289 M**	**$1,536 M**	**0**	**9.9 km²**
		Reliability (EIR)	*99%*	*Renewable Energy*	*100%*								
		Hours of Storage (avg. dmd)	*32.7*	*Self-generation*	*100%*								
18	Wind & Battery	Wind	418 MW	13%	53%	485 GWh	420.9 GWh	$0.216/kWh	$0.115/kWh	$794 M	$965 M		41.8 km²
		Battery Power	156 MW	16%	47%	216 GWh		$0.550/kWh		$495 M	$625 M		
		Battery Storage	1341 MWh										
		Power System			**100%**	**701 GWh**	**420.9 GWh**	**$0.404/kWh**		**$1,289 M**	**$1,589 M**	**0**	**41.8 km²**
		Reliability	*99%*	*Renewable Energy*	*100%*								
		Hours of Storage (avg. dmd)	*25.1*	*Self-generation*	*100%*								

Figure A.3: Power dispatch of optimal technological mixes (1/6): Atacama, Chile (Off-Grid)

Rank	System type	Daily dispatch	Yearly dispatch
1	Wind & PV & CSP Tower (Gas backup) & Diesel		
2	Wind & PV & CSP Tower & Diesel		
3	Wind & PV & CSP Tower (Gas backup) *No Diesel*		

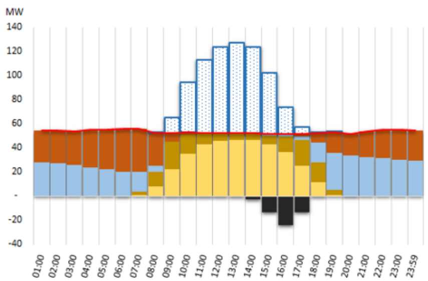
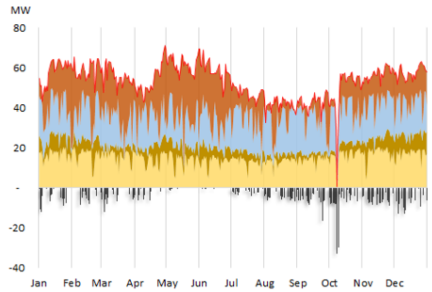
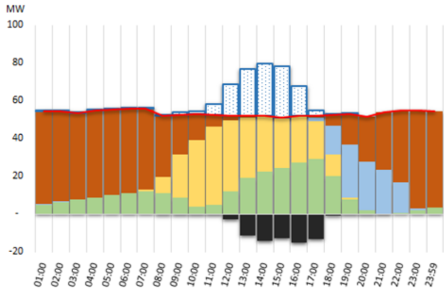
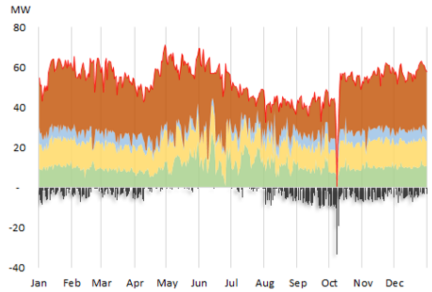
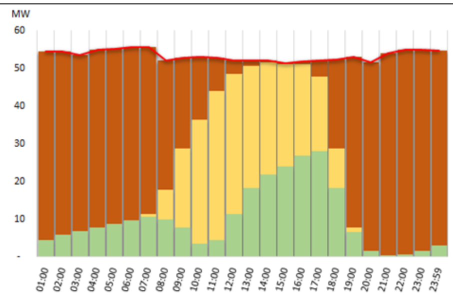
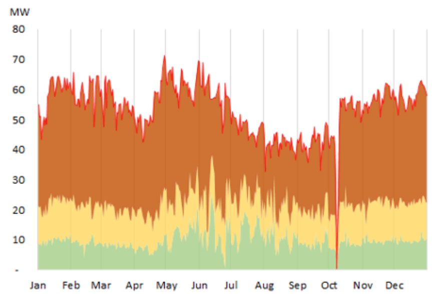
Wind | Solar PV | CSP | Storage Output | CSP Gas-backup | Grid | Gas Plant | Diesel Plant | Storage Gross Input | Spillages | Power Demand

Figure A.4: Power dispatch of optimal technological mixes (2/6): Atacama, Chile (Off-Grid)

Rank	System type	Daily dispatch	Yearly dispatch
4	CSP Tower & Diesel		
5	CSP Parabolic Trough (Gas backup) & Diesel		
6	Wind & PV & CSP Parabolic Trough & Diesel		

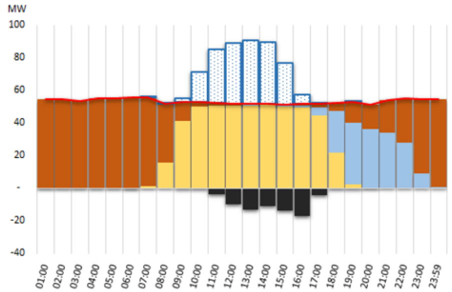
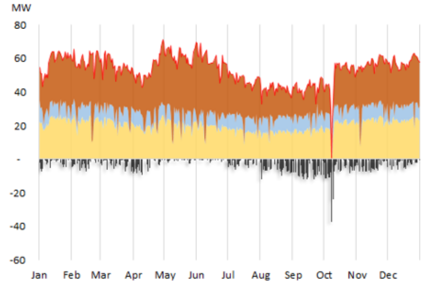
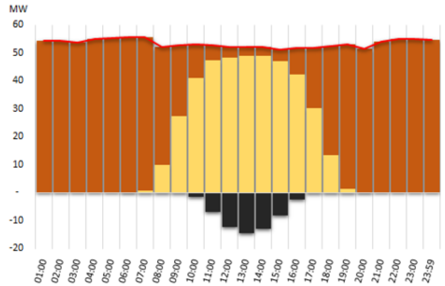
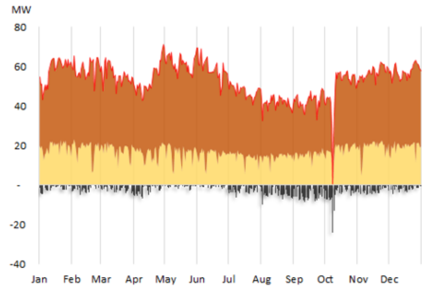
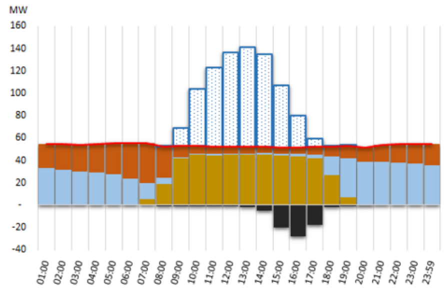
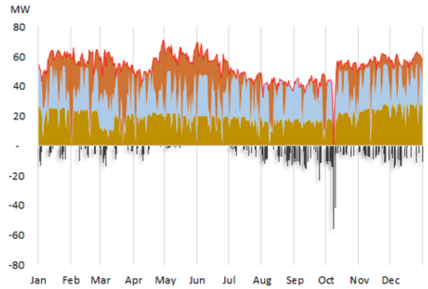
Wind, Solar PV, CSP, Storage Output, CSP Gas-backup, Grid, Gas Plant, Diesel Plant, Storage Gross Input, Spillages, Power Demand

Figure A.5: Power dispatch of optimal technological mixes (3/6): Atacama, Chile (Off-Grid)

Rank	System type	Daily dispatch	Yearly dispatch
7	PV & CSP Parabolic Trough & Diesel		
8	Wind & PV & Battery & Diesel		
9	Wind & PV & Diesel		

Wind | Solar PV | CSP | Storage Output | CSP Gas-backup | Grid | Gas Plant | Diesel Plant | Storage Gross Input | Spillages | Power Demand

Figure A.6: Power dispatch of optimal technological mixes (4/6): Atacama, Chile (Off-Grid)

Rank	System type	Daily dispatch	Yearly dispatch
10	PV & Battery & Diesel		
11 & 12	PV & Diesel		
13	CSP Parabolic Trough & Diesel		

Wind | Solar PV | CSP | Storage Output | CSP Gas-backup | Grid | Gas Plant | Diesel Plant | Storage Gross Input | Spillages | Power Demand

Figure A.7: Power dispatch of optimal technological mixes (5/6): Atacama, Chile (Off-Grid)

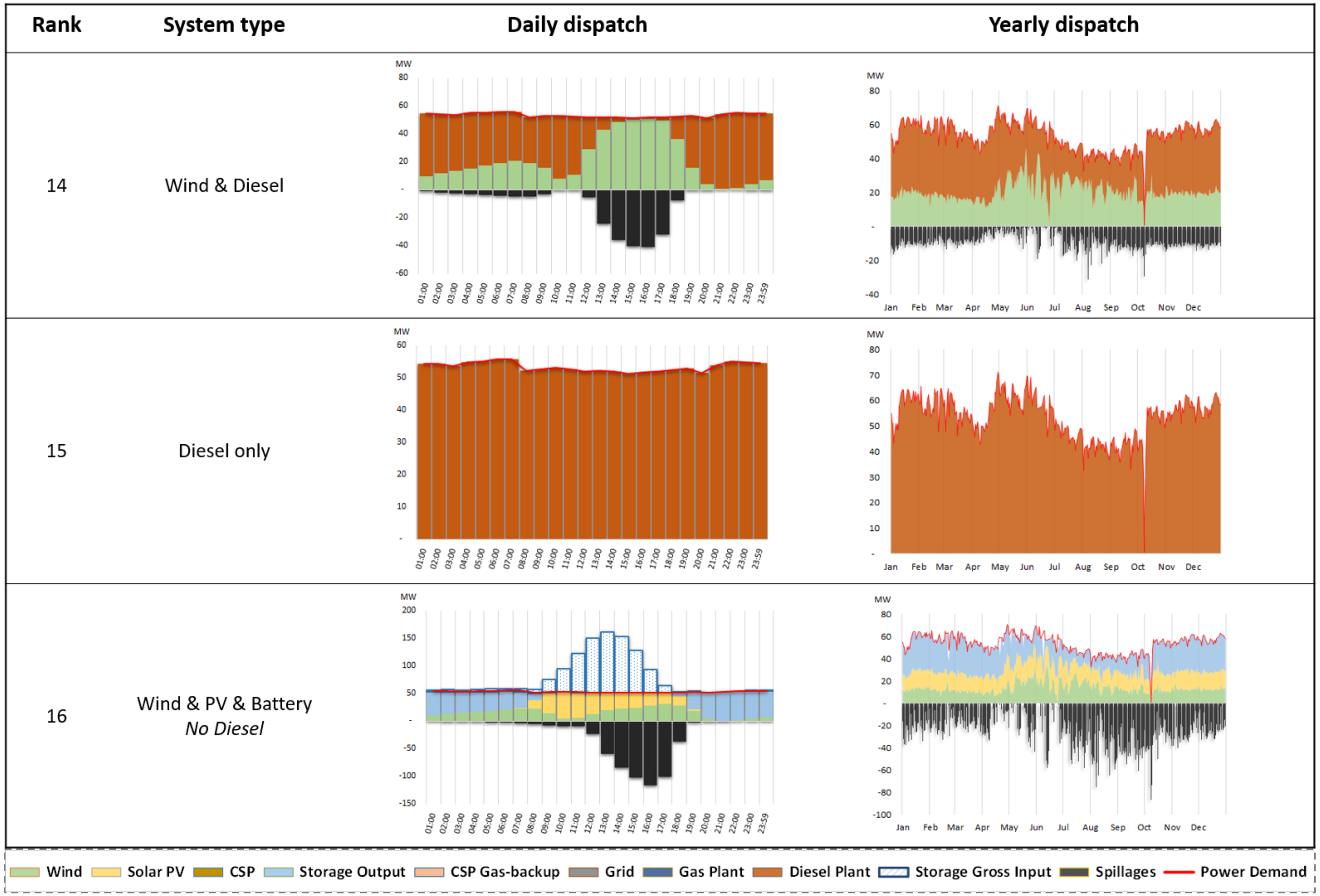
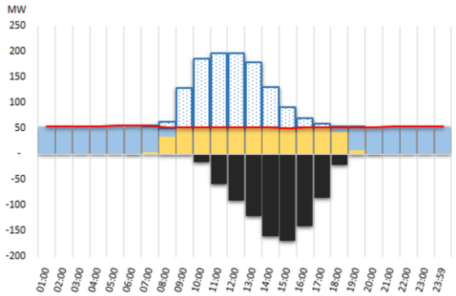
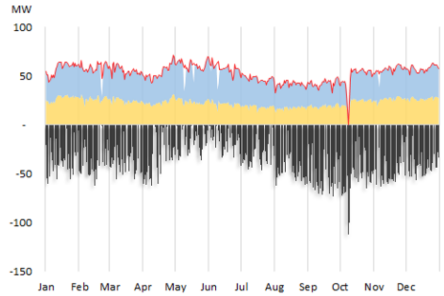
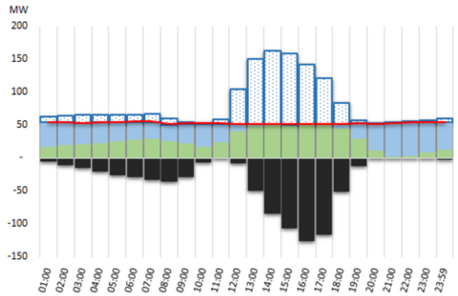
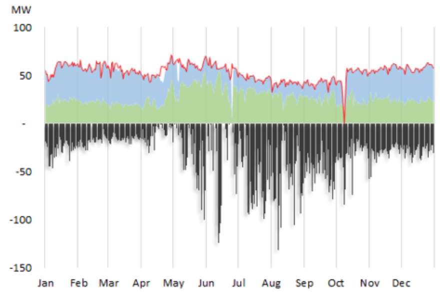


Figure A.8: Power dispatch of optimal technological mixes (6/6): Atacama, Chile (Off-Grid)

Rank	System type	Daily dispatch	Yearly dispatch
17	PV & Battery No Diesel		
15	Wind & Battery No Diesel		

Wind | Solar PV | CSP | Storage Output | CSP Gas-backup | Grid | Gas Plant | Diesel Plant | Storage Gross Input | Spillages | Power Demand

A.3 yukon, canada (off-grid)

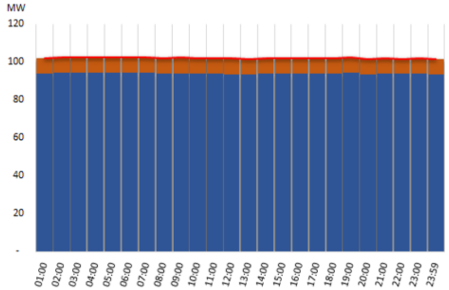
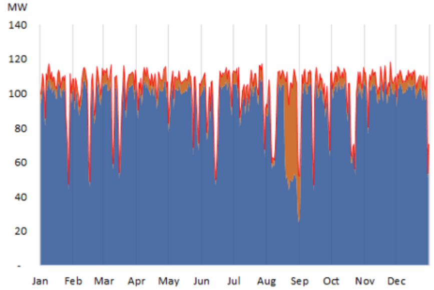
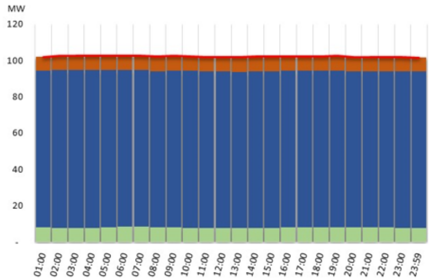
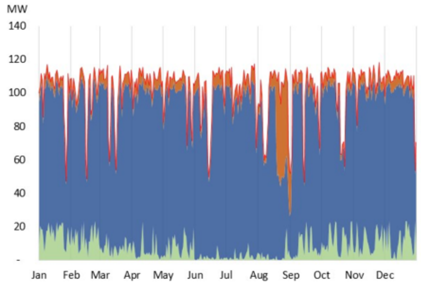
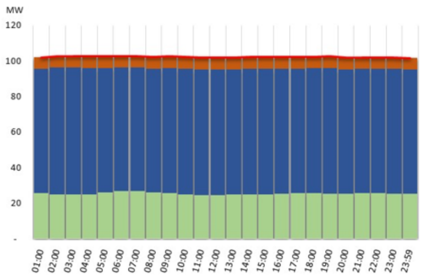
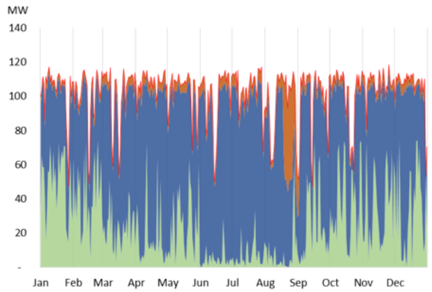
Table A.5: Detailed optimisation results (1/2): Yukon, Canada (Off-Grid)

Rank		Technology	Size	Capacity Factor	% of Total Energy Supply	Total Output (yearly)	Total Curtailment (yearly)	Net LCOE	Gross LCOE	Capital Cost	TLCC	Life Cycle Direct Emissions ($KtCO_2eq$)	Land Use (Renewable Energy only)
1	CCGT & Diesel	Diesel (rated)	77 MW	12%	8%	72 GWh		$0.427/kWh		$81 M	$271 M	1,181	
		Diesel (de-rated)	70 MW										
		CCGT (rated)	123 MW	80%	92%	824 GWh		$0.123/kWh		$197 M	$828 M	6,705	
		CCGT (de-rated)	117 MW										
		Power System			**100%**	**895 GWh**	**0.0 GWh**	**$0.150/kWh**		**$278 M**	**$1,099 M**	**7,886**	**0 km²**
		Reliability	*100%*	*Renewable Penetration*	*0%*								
		Storage Multiple	*0.0*	*Self-generation*	*100%*								
2	Wind & CCGT & Diesel (Near-Optimal 1)	Wind	31 MW	26%	8%	71 GWh	0.0 GWh	$0.131/kWh	$0.131/kWh	$68 M	$83 M		3.1 km²
		Diesel (rated)	79 MW	11%	8%	69 GWh		$0.436/kWh		$83 M	$265 M	1,131	
		Diesel (de-rated)	72 MW										
		CCGT (rated)	118 MW	77%	84%	755 GWh		$0.125/kWh		$189 M	$769 M	6,149	
		CCGT (de-rated)	112 MW										
		Power System			**100%**	**895 GWh**	**0.0 GWh**	**$0.151/kWh**		**$340 M**	**$1,117 M**	**7,280**	**3.1 km²**
		Reliability	*100%*	*Renewable Energy*	*8%*								
		Hours of Storage (avg. dmd)	*0.0*	*Self-generation*	*100%*								
3	Wind & CCGT & Diesel (Near-Optimal 2)	Wind	98 MW	8%	25%	224 GWh	1.2 GWh	$0.132/kWh	$0.131/kWh	$216 M	$262 M		9.8 km²
		Diesel (rated)	75 MW	9%	6%	56 GWh		$0.456/kWh		$79 M	$228 M	932	
		Diesel (de-rated)	68 MW										
		CCGT (rated)	123 MW	74%	69%	614 GWh		$0.134/kWh		$197 M	$669 M	5,002	
		CCGT (de-rated)	117 MW										
		Power System			**100%**	**895 GWh**	**1.2 GWh**	**$0.155/kWh**		**$492 M**	**$1,158 M**	**5,934**	**9.8 km²**
		Reliability	*100%*	*Renewable Energy*	*25%*								
		Hours of Storage (avg. dmd)	*0.0*	*Self-generation*	*100%*								
4	GT & Diesel	Diesel (rated)	80 MW	13%	9%	84 GWh		$0.415/kWh		$85 M	$307 M	1,379	
		Diesel (de-rated)	73 MW										
		GT (rated)	113 MW	84%	91%	812 GWh		$0.129/kWh		$88 M	$897 M	11,912	
		GT (de-rated)	111 MW										
		Grid	Off-Grid										
		Power System			**100%**	**895 GWh**	**0.0 GWh**	**$0.157/kWh**		**$173 M**	**$1,204 M**	**13,290**	**0 km²**
		Reliability	*100%*	*Renewable Penetration*	*0%*								
		Storage Multiple	*0.0*	*Self-generation*	*100%*								
5	Wind & PV & Diesel	Wind	153 MW	24%	36%	323 GWh	29.1 GWh	$0.143/kWh	$0.131/kWh	$337 M	$408 M		15.3 km²
		PV Tilted	116 MW	11%	12%	107 GWh	9.7 GWh	$0.224/kWh	$0.206/kWh	$191 M	$213 M		2.9 km²
		Diesel (rated)	136 MW	43%	52%	465 GWh		$0.340/kWh		$143 M	$1,400 M	7,669	
		Diesel (de-rated)	123 MW										
		Power System			**100%**	**895 GWh**	**38.8 GWh**	**$0.256/kWh**		**$671 M**	**$2,021 M**	**7,669**	**18.2 km²**
		Reliability	*100%*	*Renewable Energy*	*48%*								
		Hours of Storage (avg. dmd)	*0.0*	*Self-generation*	*100%*								
6	Wind & PV & CSP Tower & Diesel	Wind	155 MW	24%	37%	327 GWh	29.8 GWh	$0.143/kWh	$0.131/kWh	$341 M	$414 M		15.5 km²
		PV Tilted	108 MW	11%	11%	100 GWh	9.1 GWh	$0.224/kWh	$0.206/kWh	$178 M	$199 M		2.7 km²
		CSP Tower	21 MW										
		CSP Power Block	9 MW	30%	3%	23 GWh	2.9 GWh	$0.302/kWh		$55 M	$63 M	0	0.63 km²
		Thermal Storage	94 MWh										
		Diesel (rated)	137 MW	41%	50%	445 GWh		$0.342/kWh		$144 M	$1,347 M	7,341	
		Diesel (de-rated)	123 MW										
		Power System			**100%**	**895 GWh**	**41.8 GWh**	**$0.256/kWh**		**$718 M**	**$2,022 M**	**7,341**	**18.83 km²**
		Reliability	*100%*	*Renewable Energy*	*50%*	*CSP Net Eff.*	*13.3%*						
		Hours of Storage (avg. dmd)	*0.9*	*Self-generation*	*100%*	*CSP Backup*	*0.0%*						

Table A.6: Detailed optimisation results (2/2): Yukon, Canada (Off-Grid)

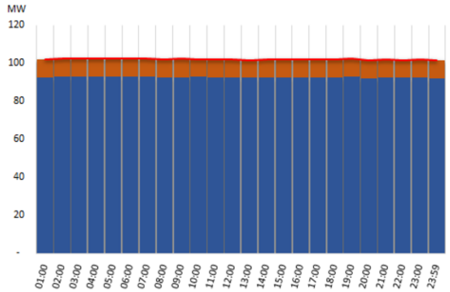
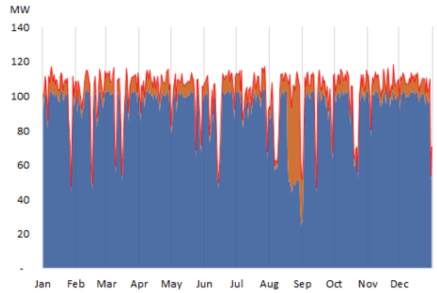
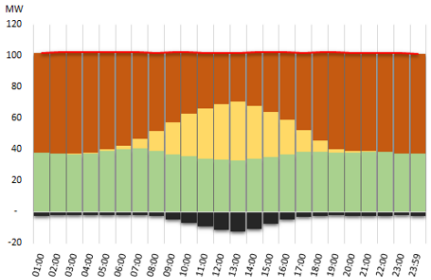
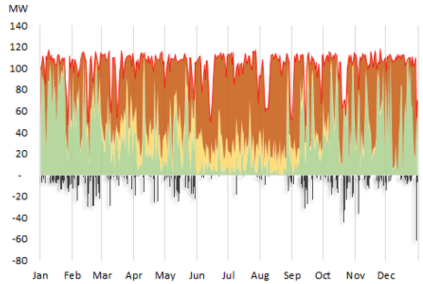
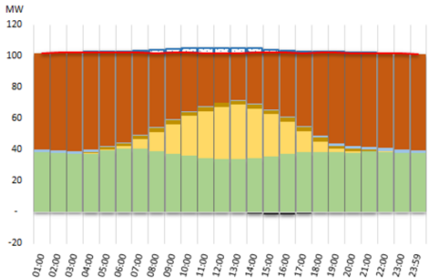
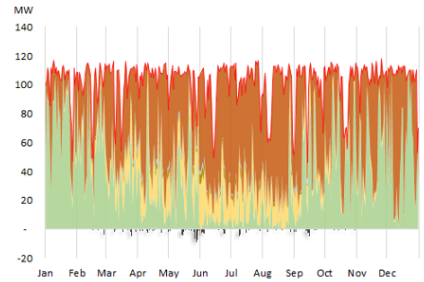
Rank		Technology	Size	Capacity Factor	% of Total Energy Supply	Total Output (yearly)	Total Curtailment (yearly)	Net LCOE	Gross LCOE	Capital Cost	TLCC	Life Cycle Direct Emissions ($KtCO_2eq$)	Land Use (Renewable Energy only)
7	Wind & CSP Tower & Diesel	Wind	155 MW	25%	38%	336 GWh	20.9 GWh	$0.139/kWh	$0.131/kWh	$341 M	$414 M		15.5 km²
		CSP Tower	132 MW										
		CSP Power Block	56 MW	31%	17%	150 GWh	15.7 GWh	$0.291/kWh		$336 M	$386 M	0	3.96 km²
		Thermal Storage	517 MWh										
		Diesel (rated)	137 MW	38%	46%	410 GWh		$0.345/kWh		$144 M	$1,251 M	6,760	
		Diesel (de-rated)	124 MW										
		Power System			**100%**	**895 GWh**	**36.6 GWh**	**$0.259/kWh**		**$821 M**	**$2,051 M**	**6,760**	**19.46 km²**
		Reliability	*100%*	*Renewable Energy*	*54%*	*CSP Net Eff.*	*13.5%*						
		Hours of Storage (avg. dmd)	*5.1*	*Self-generation*	*100%*	*CSP Backup*	*0.0%*						
8	Wind & Diesel	Wind	159 MW	24%	38%	340 GWh	25.6 GWh	$0.141/kWh	$0.131/kWh	$350 M	$424 M		15.9 km²
		Diesel (rated)	137 MW	51%	62%	555 GWh		$0.335/kWh		$144 M	$1,646 M	9,157	
		Diesel (de-rated)	124 MW										
		Power System			**100%**	**895 GWh**	**25.6 GWh**	**$0.262/kWh**		**$494 M**	**$2,071 M**	**9,157**	**15.9 km²**
		Reliability	*100%*	*Renewable Energy*	*38%*								
		Hours of Storage (avg. dmd)	*0.0*	*Self-generation*	*100%*								
9	PV & Diesel	PV Tilted	167 MW	11%	18%	158 GWh	10.6 GWh	$0.220/kWh	$0.206/kWh	$276 M	$307 M	0	4.175 km²
		Diesel (rated)	137 MW	67%	82%	737 GWh		$0.328/kWh		$145 M	$2,143 M	12,165	
		Diesel (de-rated)	125 MW										
		Power System			**100%**	**895 GWh**	**10.6 GWh**	**$0.309/kWh**		**$420 M**	**$2,450 M**	**12,165**	**4.175 km²**
		Reliability	*100%*	*Renewable Penetration*	*18%*								
		Storage Multiple	*0.0*	*Self-generation*	*100%*								
10	PV Tracking & Diesel	PV 1-Axis tracking	160 MW	12%	18%	164 GWh	10.2 GWh	$0.223/kWh	$0.210/kWh	$290 M	$324 M	0	4 km²
		Diesel (rated)	137 MW	67%	82%	731 GWh		$0.328/kWh		$145 M	$2,127 M	12,065	
		Diesel (de-rated)	125 MW										
		Power System			**100%**	**895 GWh**	**10.2 GWh**	**$0.309/kWh**		**$435 M**	**$2,451 M**	**12,065**	**4 km²**
		Reliability	*100%*	*Renewable Penetration*	*18%*								
		Storage Multiple	*0.0*	*Self-generation*	*100%*								
11	PV & CSP Tower & Diesel	*PV Tilted*	*162 MW*	*11%*	*17%*	*154 GWh*	*9.2 GWh*	*$0.218/kWh*	*$0.206/kWh*	*$267 M*	*$298 M*	*0*	*4.05 km²*
		CSP Tower	*22 MW*										
		CSP Power Block	*9 MW*	*31%*	*3%*	*24 GWh*	*3.4 GWh*	*$0.306/kWh*		*$57 M*	*$66 M*	*0*	*0.66 km²*
		Thermal Storage	*104 MWh*										
		Diesel (rated)	*137 MW*	*67%*	*82%*	*735 GWh*		*$0.328/kWh*		*$145 M*	*$2,136 M*	*12,121*	
		Diesel (de-rated)	*125 MW*										
		Power System			***100%***	***895 GWh***	***10.2 GWh***	***$0.309/kWh***		***$427 M***	***$2,451 M***	***12,121***	***4.225 km²***
		Reliability	*100%*	*Renewable Penetration*	*20%*	*CSP Net Eff.*	*13.2%*						
		Storage Multiple	*1.0*	*Self-generation*	*100%*	*CSP Backup*	*0.0%*						
12	CSP Tower & Diesel	*CSP Tower*	*247 MW*										
		CSP Power Block	*101 MW*	*32%*	*32%*	*284 GWh*	*26.4 GWh*	*$0.281/kWh*		*$614 M*	*$707 M*	*0*	*7.41 km²*
		Thermal Storage	*841 MWh*										
		Diesel (rated)	*137 MW*	*56%*	*68%*	*613 GWh*		*$0.332/kWh*		*$145 M*	*$1,804 M*	*10,107*	
		Diesel (de-rated)	*125 MW*										
		Power System			***100%***	***895 GWh***	***26.2 GWh***	***$0.316/kWh***		***$754 M***	***$2,505 M***	***10,107***	***7.38 km²***
		Reliability	*100%*	*Renewable Penetration*	*32%*	*CSP Net Eff.*	*13.7%*						
		Storage Multiple	*8.2*	*Self-generation*	*100%*	*CSP Backup*	*0.0%*		8.22855908				
13	Diesel only	*Diesel (rated)*	*137 MW*	*82%*	*100%*	*895 GWh*		*$0.325/kWh*		*$145 M*	*$2,574 M*	*14,773*	
		Diesel (de-rated)	*125 MW*										
		Power System			***100%***	***895 GWh***	***0.0 GWh***	***$0.325/kWh***		***$145 M***	***$2,574 M***	***14,773***	***0 km²***
		Reliability	*100%*	*Renewable Penetration*	*0%*								
		Storage Multiple	*0.0*	*Self-generation*	*100%*								

Figure A.9: Power dispatch of optimal technological mixes (1/4): Yukon, Canada (Off-Grid)

Rank	System type	Daily dispatch	Yearly dispatch
1	CCGT & Diesel		
2	Wind & CCGT & Diesel *Near Optimal 1*		
3	Wind & CCGT & Diesel *Near Optimal 2*		

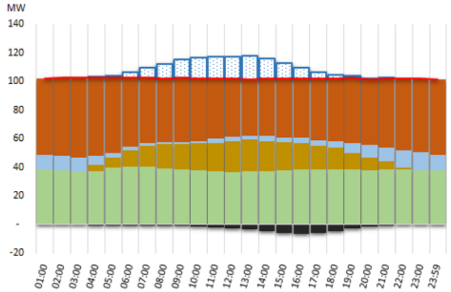
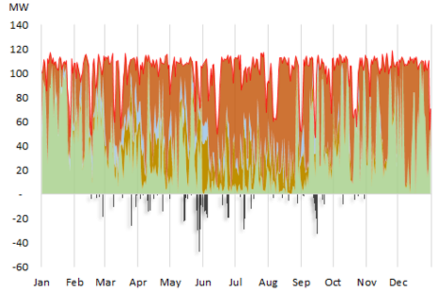
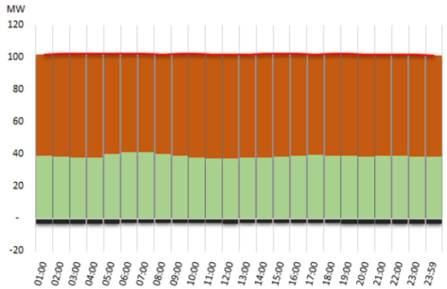
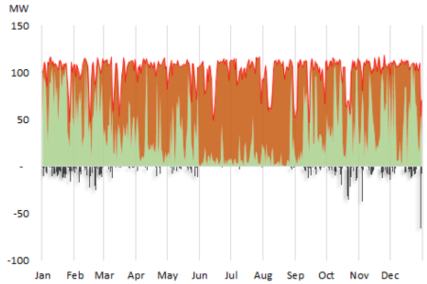
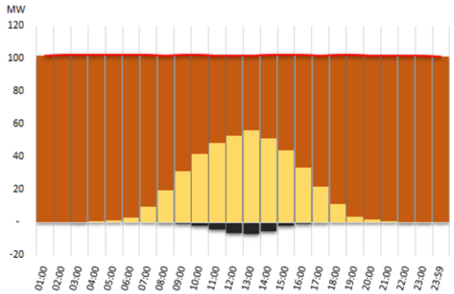
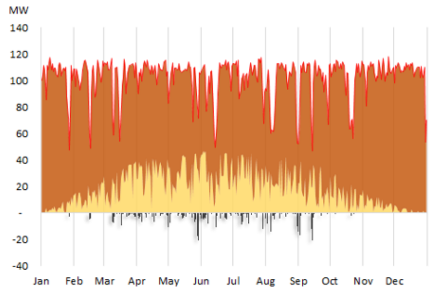
Wind · Solar PV · CSP · Storage Output · CSP Gas-backup · Grid · Gas Plant · Diesel Plant · Storage Gross Input · Spillages · Power Demand

Figure A.10: Power dispatch of optimal technological mixes (2/4): Yukon, Canada (Off-Grid)

Rank	System type	Daily dispatch	Yearly dispatch
5	GT & Diesel		
5	Wind & PV & Diesel		
6	Wind & PV & CSP Tower & Diesel		

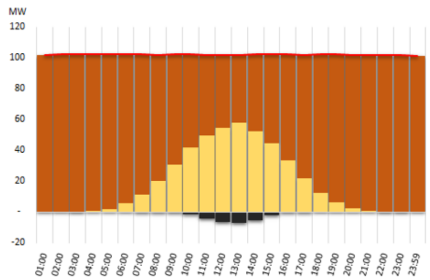
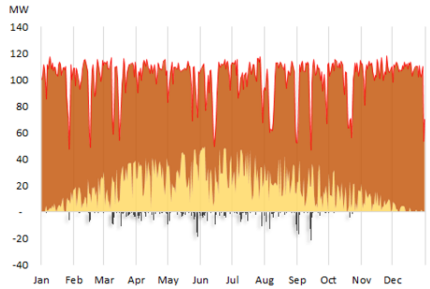
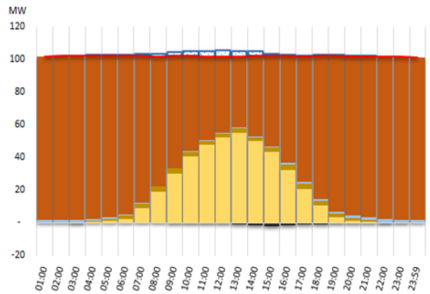
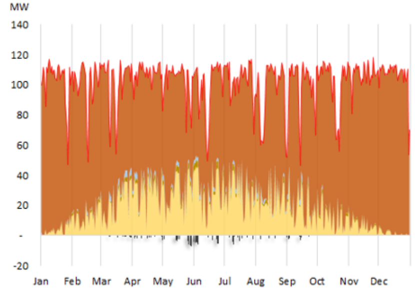
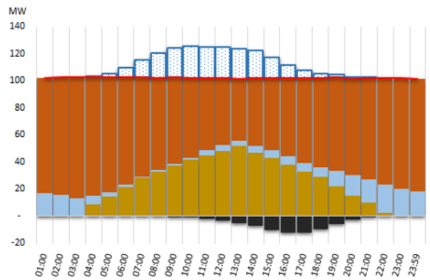
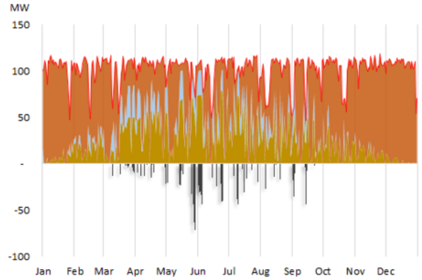
Wind Solar PV CSP Storage Output CSP Gas-backup Grid Gas Plant Diesel Plant Storage Gross Input Spillages Power Demand

Figure A.11: Power dispatch of optimal technological mixes (3/4): Yukon, Canada (Off-Grid)

Rank	System type	Daily dispatch	Yearly dispatch
7	Wind & CSP Tower & Diesel		
8	Wind & Diesel		
9	PV & Diesel		

Wind, Solar PV, CSP, Storage Output, CSP Gas-backup, Grid, Gas Plant, Diesel Plant, Storage Gross Input, Spillages, Power Demand

Figure A.12: Power dispatch of optimal technological mixes (4/4): Yukon, Canada (Off-Grid)

Rank	System type	Daily dispatch	Yearly dispatch
10	PV Tracking & Diesel		
11	PV & CSP Tower & Diesel		
12	CSP Tower & Diesel		

Wind | Solar PV | CSP | Storage Output | CSP Gas-backup | Grid | Gas Plant | Diesel Plant | Storage Gross Input | Spillages | Power Demand

A.4 NORTH-WESTERN AUSTRALIA (OFF-GRID)

Table A.7: Detailed optimisation results (1/3): North-Western Australia (Off-Grid)

Rank	Technology		Size	Capacity Factor	% of Total Energy Supply	Total Output (yearly)	Total Curtailment (yearly)	Net LCOE	Gross LCOE	Capital Cost	TLCC	Life Cycle Direct Emissions ($KtCO_2eq$)	Land Use (Renewable Energy only)
1	CSP Tower (Gas backup) & Diesel	CSP Tower	43 MW										
		CSP Power Block	16 MW	86%	98%	120 GWh	8.4 GWh	$0.173/kWh		$108 M	$166 M	317	1.29 km^2
		Thermal Storage	191 MWh										
		Diesel (rated)	9 MW	2%	2%	2 GWh		$0.894/kWh		$9 M	$13 M	23	
		Diesel (de-rated)	8 MW										
		Power System			**100%**	**122 GWh**	**8.4 GWh**	**$0.184/kWh**		**$117 M**	**$179 M**	**340**	**1.29 km^2**
		Reliability	*100%*	*Renewable Energy*	*76%*	*CSP Net Eff.*	*13.7%*						
		Hours of Storage (avg. dmd)	*13.7*	*Self-generation*	*100%*	*CSP Backup*	*22.9%*						
2	Wind & PV & CSP Tower (Gas backup)	PV Tilted	18 MW	21%	27%	33 GWh	1.4 GWh	$0.122/kWh	$0.117/kWh	$30 M	$33 M		0.45 km^2
		CSP Tower	23 MW										
		CSP Power Block	29 MW	35%	73%	88 GWh	1.0 GWh	$0.237/kWh		$95 M	$171 M	641	0.69 km^2
		Thermal Storage	188 MWh										
		Power System			**100%**	**122 GWh**	**2.4 GWh**	**$0.206/kWh**		**$125 M**	**$204 M**	**641**	**1.14 km^2**
		Reliability (EIR)	*99.91%*	*Renewable Energy*	*68%*	*CSP Net Eff.*	*13.8%*						
		Hours of Storage (avg. dmd)	*13.5*	*Self-generation*	*100%*	*CSP Backup*	*31.6%*						
3	Wind & PV & CSP Tower & Diesel	Wind	3 MW	22%	5%	6 GWh	0.1 GWh	$0.146/kWh	$0.144/kWh	$6 M	$7 M		0.3 km^2
		PV Tilted	12 MW	22%	19%	23 GWh	0.4 GWh	$0.119/kWh	$0.117/kWh	$20 M	$22 M		0.3 km^2
		CSP Tower	37 MW										
		CSP Power Block	14 MW	60%	60%	74 GWh	12.9 GWh	$0.189/kWh		$99 M	$111 M	0	1.11 km^2
		Thermal Storage	225 MWh										
		Diesel (rated)	18 MW	13%	16%	20 GWh		$0.403/kWh		$19 M	$63 M	250	
		Diesel (de-rated)	17 MW										
		Power System			**100%**	**122 GWh**	**13.3 GWh**	**$0.208/kWh**		**$143 M**	**$203 M**	**250**	**1.71 km^2**
		Reliability	*100%*	*Renewable Energy*	*84%*	*CSP Net Eff.*	*12.7%*						
		Hours of Storage (avg. dmd)	*16.2*	*Self-generation*	*100%*	*CSP Backup*	*0.0%*						
4	Wind & PV Tracking & CSP Tower & Diesel	Wind	4 MW	22%	6%	8 GWh	0.0 GWh	$0.145/kWh	$0.144/kWh	$8 M	$9 M		0.4 km^2
		PV 1-Axis tracking	7 MW	23%	11%	14 GWh	0.1 GWh	$0.125/kWh	$0.124/kWh	$13 M	$14 M		0.175 km^2
		CSP Tower	41 MW										
		CSP Power Block	14 MW	66%	67%	81 GWh	14.8 GWh	$0.183/kWh		$105 M	$119 M	0	1.23 km^2
		Thermal Storage	229 MWh										
		Diesel (rated)	18 MW	13%	16%	19 GWh		$0.406/kWh		$19 M	$62 M	243	
		Diesel (de-rated)	17 MW										
		Power System			**100%**	**122 GWh**	**15.0 GWh**	**$0.209/kWh**		**$144 M**	**$204 M**	**243**	**1.805 km^2**
		Reliability	*100%*	*Renewable Energy*	*84%*	*CSP Net Eff.*	*12.6%*						
		Hours of Storage (avg. dmd)	*16.5*	*Self-generation*	*100%*	*CSP Backup*	*0.0%*						
5	PV & CSP Tower & Diesel	PV Tilted	14 MW	22%	22%	27 GWh	0.5 GWh	$0.119/kWh	$0.117/kWh	$23 M	$25 M		0.35 km^2
		CSP Tower	39 MW										
		CSP Power Block	15 MW	58%	63%	77 GWh	14.4 GWh	$0.191/kWh		$104 M	$118 M	0	1.17 km^2
		Thermal Storage	235 MWh										
		Diesel (rated)	18 MW	12%	15%	18 GWh		$0.412/kWh		$19 M	$61 M	235	
		Diesel (de-rated)	17 MW										
		Power System			**100%**	**122 GWh**	**14.9 GWh**	**$0.209/kWh**		**$146 M**	**$204 M**	**235**	**1.52 km^2**
		Reliability	*100%*	*Renewable Energy*	*85%*	*CSP Net Eff.*	*12.6%*						
		Hours of Storage (avg. dmd)	*16.9*	*Self-generation*	*100%*	*CSP Backup*	*0.0%*						
6	Wind & CSP Tower & Diesel	Wind	2 MW	22%	3%	4 GWh	0.0 GWh	$0.144/kWh	$0.144/kWh	$4 M	$4 M		0.2 km^2
		CSP Tower	49 MW										
		CSP Power Block	15 MW	76%	82%	100 GWh	14.6 GWh	$0.175/kWh		$124 M	$140 M	0	1.47 km^2
		Thermal Storage	283 MWh										
		Diesel (rated)	18 MW	10%	16%	15 GWh		$0.437/kWh		$19 M	$53 M	195	
		Diesel (de-rated)	17 MW										
		Power System			**100%**	**122 GWh**	**14.6 GWh**	**$0.209/kWh**		**$147 M**	**$204 M**	**230**	**1.67 km^2**
		Reliability	*100%*	*Renewable Energy*	*85%*	*CSP Net Eff.*	*13.0%*						
		Hours of Storage (avg. dmd)	*20.4*	*Self-generation*	*100%*	*CSP Backup*	*0.0%*						

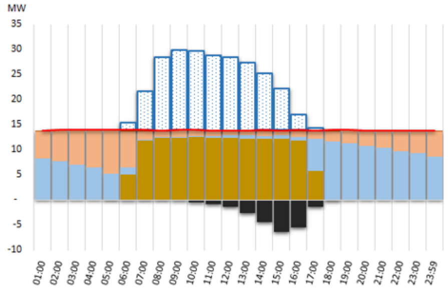
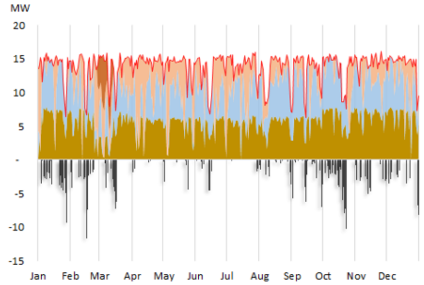
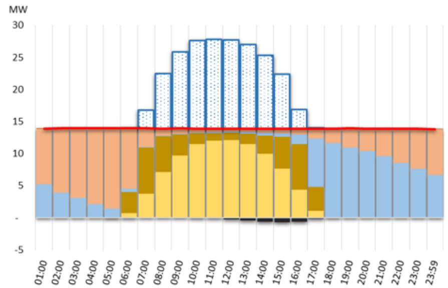
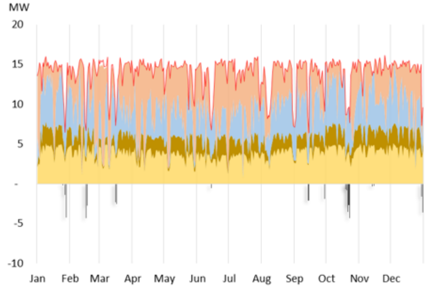
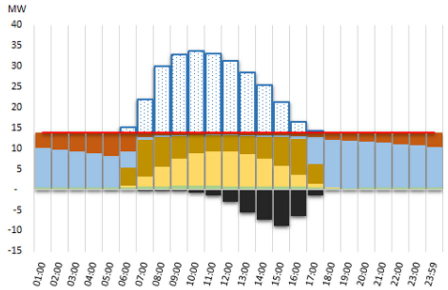
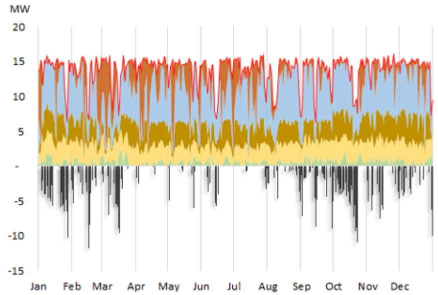
Table A.8: Detailed optimisation results (2/3): North-Western Australia (Off-Grid)

Rank	Technology		Size	Capacity Factor	% of Total Energy Supply	Total Output (yearly)	Total Curtailment (yearly)	Net LCOE	Gross LCOE	Capital Cost	TLCC	Life Cycle Direct Emissions ($KtCO_2eq$)	Land Use (Renewable Energy only)
7	CSP Tower & Diesel	CSP Tower	52 MW	75%	86%	105 GWh	16.3 GWh	$0.177/kWh		$132 M	$149 M	0	1.56 km²
		CSP Power Block	16 MW										
		Thermal Storage	303 MWh										
		Diesel (rated)	18 MW	11%	14%	17 GWh		$0.425/kWh		$19 M	$56 M	211	
		Diesel (de-rated)	17 MW										
		Power System			**100%**	**122 GWh**	**16.3 GWh**	**$0.210/kWh**		**$151 M**	**$206 M**	**211**	**1.56 km²**
		Reliability	*100%*	*Renewable Energy*	*86%*	*CSP Net Eff.*	*12.9%*						
		Hours of Storage (avg. dmd)	*21.8*	*Self-generation*	*100%*	*CSP Backup*	*0.0%*						
8	Wind & PV & CSP Parabolic Trough & Diesel	Wind	15 MW	19%	21%	26 GWh	3.3 GWh	$0.162/kWh	$0.144/kWh	$29 M	$34 M		1.5 km²
		PV Tilted	15 MW	20%	21%	26 GWh	3.2 GWh	$0.132/kWh	$0.117/kWh	$25 M	$27 M		0.375 km²
		CSP Parabolic troughs	15 MW	55%	20%	24 GWh	2.7 GWh	$0.265/kWh		$45 M	$51 M	0	0.45 km²
		CSP Power Block	5 MW										
		Thermal Storage	74 MWh										
		Diesel (rated)	17 MW	32%	38%	46 GWh		$0.338/kWh		$18 M	$124 M	586	
		Diesel (de-rated)	16 MW										
		Power System			**100%**	**122 GWh**	**9.2 GWh**	**$0.244/kWh**		**$117 M**	**$236 M**	**586**	**2.325 km²**
		Reliability	*100%*	*Renewable Energy*	*62%*	*CSP Net Eff.*	*17.0%*						
		Hours of Storage (avg. dmd)	*5.3*	*Self-generation*	*100%*	*CSP Backup*	*0.0%*						
9	Wind & PV & Battery & Diesel	Wind	21 MW	18%	26%	34 GWh	7.0 GWh	$0.174/kWh	$0.144/kWh	$40 M	$47 M		2.1 km²
		PV Tilted	21 MW	19%	26%	34 GWh	7.0 GWh	$0.142/kWh	$0.117/kWh	$35 M	$38 M		0.525 km²
		Battery Power	4 MW	13%	4%	4 GWh		$0.446/kWh		$8 M	$10 M		
		Battery Storage	21 MWh										
		Diesel (rated)	18 MW	37%	45%	55 GWh		$0.332/kWh		$19 M	$145 M	698	
		Diesel (de-rated)	17 MW										
		Power System			**100%**	**127 GWh**	**14.0 GWh**	**$0.249/kWh**		**$101 M**	**$240 M**	**698**	**2.625 km²**
		Reliability	*100%*	*Renewable Energy*	*57%*								
		Hours of Storage (avg. dmd)	*1.5*	*Self-generation*	*100%*								
10	Wind & PV & Diesel	Wind	22 MW	16%	27%	33 GWh	10.3 GWh	$0.189/kWh	$0.144/kWh	$42 M	$49 M		2.2 km²
		PV Tilted	21 MW	17%	25%	31 GWh	9.7 GWh	$0.154/kWh	$0.117/kWh	$35 M	$38 M		0.525 km²
		Diesel (rated)	18 MW	40%	48%	58 GWh		$0.329/kWh		$19 M	$154 M	744	
		Diesel (de-rated)	17 MW										
		Power System			**100%**	**122 GWh**	**20.0 GWh**	**$0.251/kWh**		**$95 M**	**$241 M**	**744**	**2.725 km²**
		Reliability	*100%*	*Renewable Energy*	*52%*								
		Hours of Storage (avg. dmd)	*0.0*	*Self-generation*	*100%*								
11	PV & CSP Parabolic Trough & Diesel	PV Tilted	26 MW	18%	34%	41 GWh	8.8 GWh	$0.142/kWh	$0.117/kWh	$43 M	$47 M		0.65 km²
		CSP Parabolic troughs	25 MW	55%	32%	39 GWh	5.6 GWh	$0.275/kWh		$76 M	$86 M	0	0.75 km²
		CSP Power Block	8 MW										
		Thermal Storage	127 MWh										
		Diesel (rated)	18 MW	28%	34%	42 GWh		$0.345/kWh		$19 M	$114 M	529	
		Diesel (de-rated)	17 MW										
		Power System			**100%**	**122 GWh**	**14.5 GWh**	**$0.255/kWh**		**$137 M**	**$247 M**	**529**	**1.4 km²**
		Reliability	*100%*	*Renewable Energy*	*66%*	*CSP Net Eff.*	*16.5%*						
		Hours of Storage (avg. dmd)	*9.1*	*Self-generation*	*100%*	*CSP Backup*	*0.0%*						
12	PV & Diesel	PV Tilted	23 MW	19%	32%	39 GWh	5.3 GWh	$0.133/kWh	$0.117/kWh	$38 M	$42 M		0.575 km²
		Diesel (rated)	18 MW	56%	68%	83 GWh		$0.319/kWh		$19 M	$210 M	1,053	
		Diesel (de-rated)	17 MW										
		Power System			**100%**	**122 GWh**	**5.3 GWh**	**$0.260/kWh**		**$57 M**	**$252 M**	**1,053**	**0.575 km²**
		Reliability	*100%*	*Renewable Energy*	*32%*								
		Hours of Storage (avg. dmd)	*13.2*	*Self-generation*	*100%*								

Table A.9: Detailed optimisation results (3/3): North-Western Australia (Off-Grid)

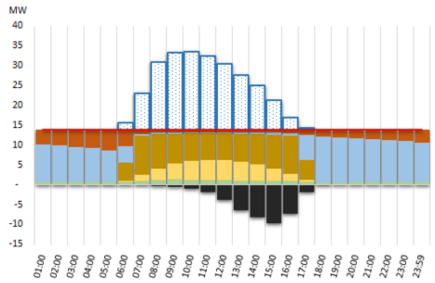
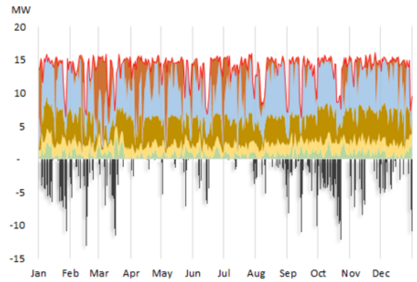
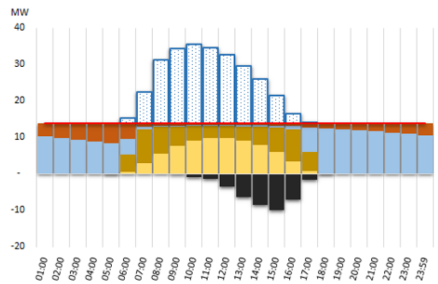
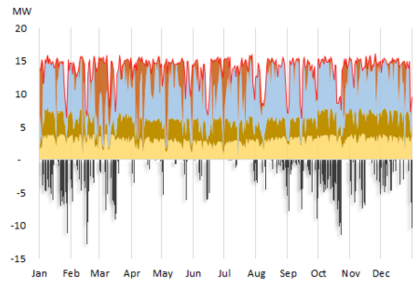
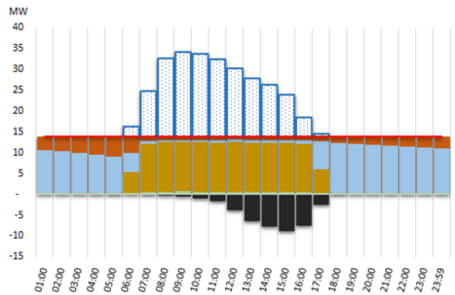
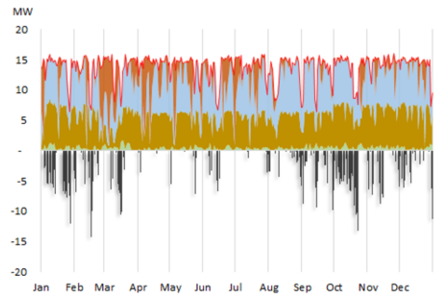
Rank	Technology		Size	Capacity Factor	% of Total Energy Supply	Total Output (yearly)	Total Curtailment (yearly)	Net LCOE	Gross LCOE	Capital Cost	TLCC	Life Cycle Direct Emissions ($KtCO_2eq$)	Land Use (Renewable Energy only)
13	PV Tracking & Diesel	PV 1-Axis tracking	22 MW	20%	32%	39 GWh	4.9 GWh	$0.140/kWh	$0.124/kWh	$40 M	$44 M		0.55 km²
		Diesel (rated)	18 MW	56%	68%	83 GWh		$0.319/kWh		$19 M	$210 M	1,053	
		Diesel (de-rated)	17 MW										
		Power System			**100%**	**122 GWh**	**4.9 GWh**	**$0.262/kWh**		**$59 M**	**$254 M**	**1,053**	**0.55 km²**
		Reliability	*100%*	*Renewable Energy*	*32%*								
		Hours of Storage (avg. dmd)	*13.2*	*Self-generation*	*100%*								
14	PV & Battery & Diesel	PV Tilted	37 MW	20%	38%	65 GWh	7.0 GWh	$0.130/kWh	$0.117/kWh	$61 M	$67 M		0.925 km²
		Battery Power	13 MW	15%	14%	17 GWh		$0.396/kWh		$27 M	$33 M		
		Battery Storage	72 MWh										
		Diesel (rated)	18 MW	40%	48%	59 GWh		$0.329/kWh		$19 M	$155 M	751	
		Diesel (de-rated)	17 MW										
		Power System			**100%**	**140 GWh**	**7.0 GWh**	**$0.264/kWh**		**$107 M**	**$255 M**	**751**	**0.925 km²**
		Reliability	*100%*	*Renewable Energy*	*58%*								
		Hours of Storage (avg. dmd)	*5.2*	*Self-generation*	*100%*								
15	Wind & Diesel	Wind	29 MW	19%	39%	47 GWh	9.2 GWh	$0.172/kWh	$0.144/kWh	$55 M	$65 M		2.9 km²
		Diesel (rated)	18 MW	50%	61%	75 GWh		$0.321/kWh		$19 M	$191 M	950	
		Diesel (de-rated)	17 MW										
		Power System			**100%**	**122 GWh**	**9.2 GWh**	**$0.265/kWh**		**$74 M**	**$256 M**	**950**	**2.9 km²**
		Reliability	*100%*	*Renewable Energy*	*39%*								
		Hours of Storage (avg. dmd)	*5.5*	*Self-generation*	*100%*								
16	CSP Parabolic Trough & Diesel	CSP Parabolic troughs	55 MW	69%	75%	91 GWh	8.3 GWh	$0.232/kWh		$149 M	$169 M	0	1.65 km²
		CSP Power Block	15 MW										
		Thermal Storage	204 MWh										
		Diesel (rated)	18 MW	21%	25%	31 GWh		$0.363/kWh		$19 M	$90 M	396	
		Diesel (de-rated)	17 MW										
		Power System			**100%**	**122 GWh**	**8.3 GWh**	**$0.265/kWh**		**$168 M**	**$259 M**	**396**	**1.65 km²**
		Reliability	*100%*	*Renewable Energy*	*75%*	*CSP Net Eff.*	*17.5%*						
		Hours of Storage (avg. dmd)	*14.7*	*Self-generation*	*100%*	*CSP Backup*	*0.0%*						
17	Diesel only	Diesel (rated)	18 MW	82%	100%	122 GWh		$0.310/kWh		$19 M	$302 M	1,553	
		Diesel (de-rated)	17 MW										
		Power System			**100%**	**122 GWh**	**0.0 GWh**	**$0.310/kWh**		**$19 M**	**$302 M**	**1,553**	**0 km²**
		Reliability	*100%*	*Renewable Energy*	*0%*								
		Hours of Storage (avg. dmd)	*8.6*	*Self-generation*	*100%*								
18	Wind & PV & Battery	Wind	17 MW	14%	10%	21 GWh	11.8 GWh	$0.223/kWh	$0.144/kWh	$32 M	$38 M		1.7 km²
		PV Tilted	84 MW	14%	47%	105 GWh	57.8 GWh	$0.182/kWh	$0.117/kWh	$139 M	$152 M		2.1 km²
		Battery Power	41 MW	15%	43%	52 GWh		$0.587/kWh		$131 M	$159 M		
		Battery Storage	354 MWh										
		Power System			**100%**	**178 GWh**	**69.6 GWh**	**$0.381/kWh**		**$302 M**	**$349 M**	**0**	**3.8 km²**
		Reliability	*99%*	*Renewable Energy*	*100%*								
		Hours of Storage (avg. dmd)	*25.5*	*Self-generation*	*100%*								
19	PV & Battery	PV Tilted	83 MW	18%	44%	128 GWh	32.9 GWh	$0.148/kWh	$0.117/kWh	$137 M	$150 M		2.075 km²
		Battery Power	43 MW	18%	56%	68 GWh		$0.736/kWh		$256 M	$311 M		
		Battery Storage	713 MWh										
		Power System			**100%**	**195 GWh**	**32.9 GWh**	**$0.490/kWh**		**$393 M**	**$462 M**	**0**	**2.075 km²**
		Reliability	*99%*	*Renewable Energy*	*100%*								
		Hours of Storage (avg. dmd)	*51.3*	*Self-generation*	*100%*								

Figure A.13: Power dispatch of optimal technological mixes (1/6): North-Western Australia (Off-Grid)

Rank	System type	Daily dispatch	Yearly dispatch
1	CSP Tower (Gas backup) & Diesel		
2	PV & CSP Tower (Gas backup) *No Diesel*		
3	Wind & PV & CSP Tower & Diesel		

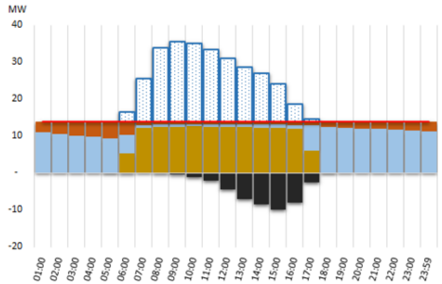
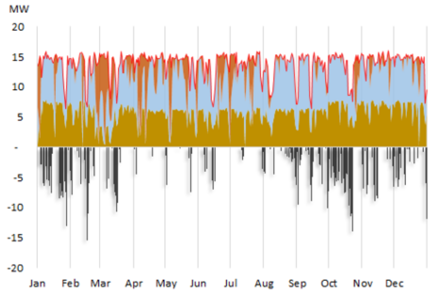
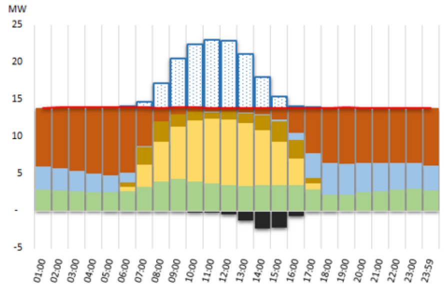
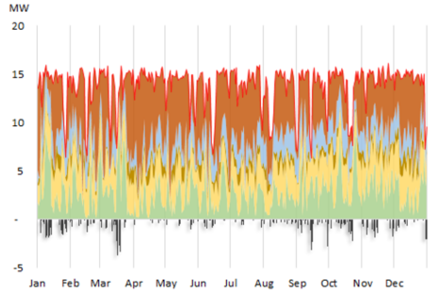
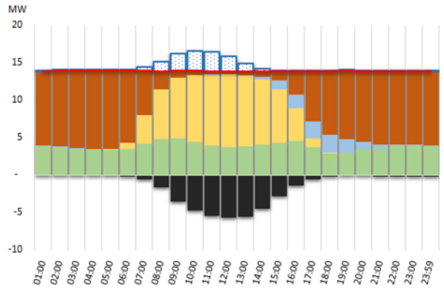
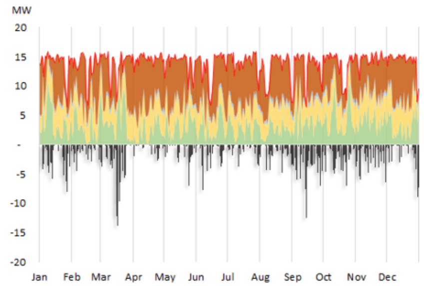
Wind | Solar PV | CSP | Storage Output | CSP Gas-backup | Grid | Gas Plant | Diesel Plant | Storage Gross Input | Spillages | Power Demand

Figure A.14: Power dispatch of optimal technological mixes (2/6): North-Western Australia (Off-Grid)

Rank	System type	Daily dispatch	Yearly dispatch
4	Wind & PV Tracking & CSP Tower & Diesel		
5	PV & CSP Tower & Diesel		
6	Wind & CSP Tower & Diesel		

Wind | Solar PV | CSP | Storage Output | CSP Gas-backup | Grid | Gas Plant | Diesel Plant | Storage Gross Input | Spillages | Power Demand

Figure A.15: Power dispatch of optimal technological mixes (3/6): North-Western Australia (Off-Grid)

Rank	System type	Daily dispatch	Yearly dispatch
7	CSP Tower & Diesel		
8	Wind & PV & CSP Parabolic Trough & Diesel		
9	Wind & PV & Battery & Diesel		

Wind, Solar PV, CSP, Storage Output, CSP Gas-backup, Grid, Gas Plant, Diesel Plant, Storage Gross Input, Spillages, Power Demand

Figure A.16: Power dispatch of optimal technological mixes (4/6): North-Western Australia (Off-Grid)

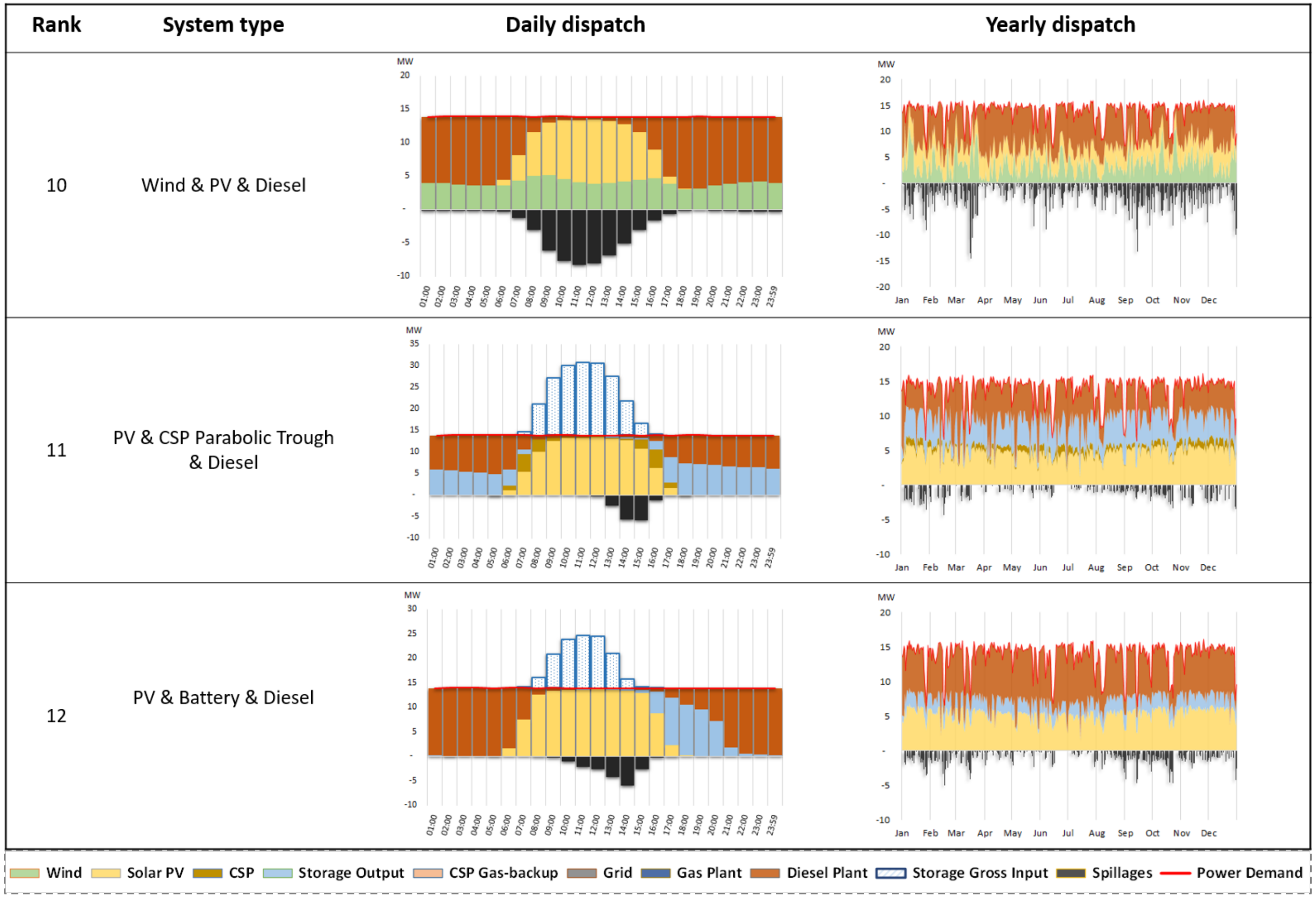
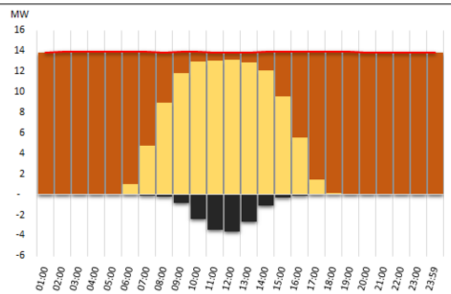
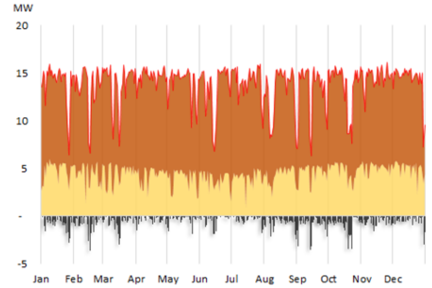
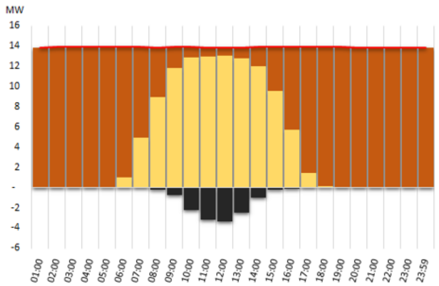
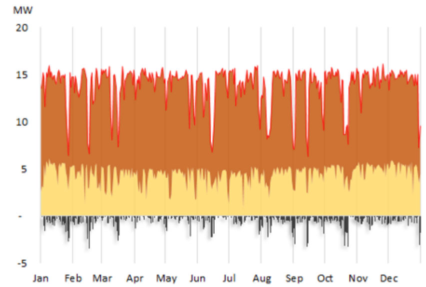
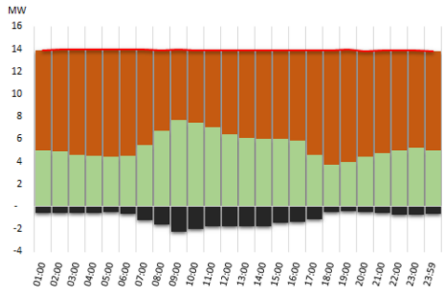
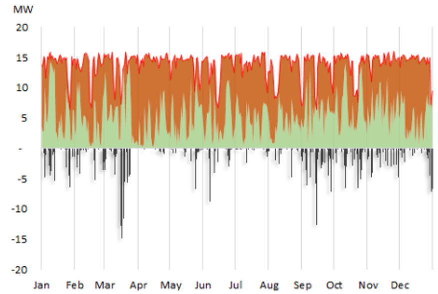
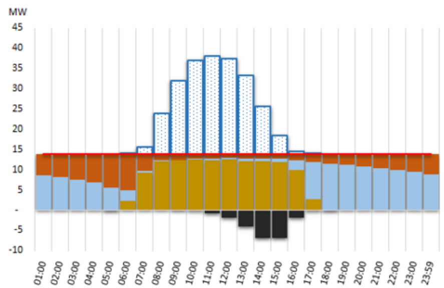
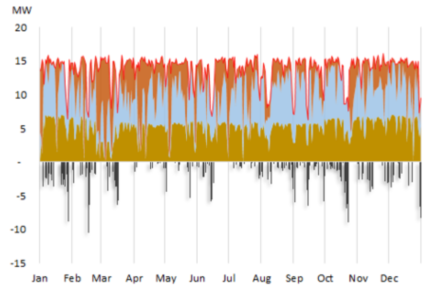
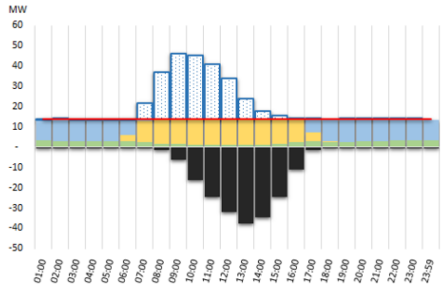
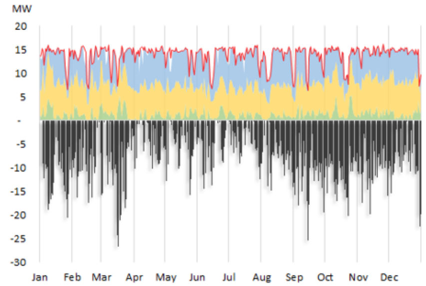
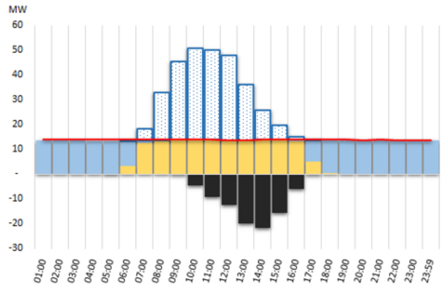
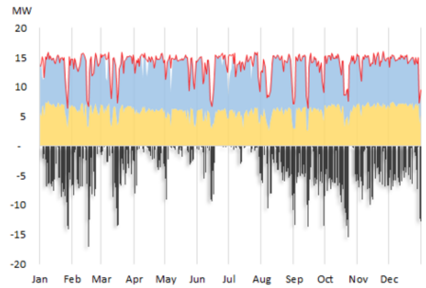


Figure A.17: Power dispatch of optimal technological mixes (5/6): North-Western Australia (Off-Grid)

Rank	System type	Daily dispatch	Yearly dispatch
13	PV & Diesel		
14	PV Tracking & Diesel		
15	Wind & Diesel		

Wind · Solar PV · CSP · Storage Output · CSP Gas-backup · Grid · Gas Plant · Diesel Plant · Storage Gross Input · Spillages · Power Demand

Figure A.18: Power dispatch of optimal technological mixes (6/6): North-Western Australia (Off-Grid)

Rank	System type	Daily dispatch	Yearly dispatch
16	CSP Parabolic Trough & Diesel		
18	Wind & PV & Battery *No Diesel*		
19	PV & Battery *No Diesel*		

Wind | Solar PV | CSP | Storage Output | CSP Gas-backup | Grid | Gas Plant | Diesel Plant | Storage Gross Input | Spillages | Power Demand

B

ADEQUACY ANALYSIS - SELECTION OF CLIMATE DATA

This appendix contains additional solar and wind data that have been used in the adequacy analysis in chapter 6 on page 163. Specifically, a data table is provided with key climate metrics along with a plot representing weekly average resource inputs (solar insolation or wind speed) for 10 year of data.

B.1 ATACAMA, CHILE

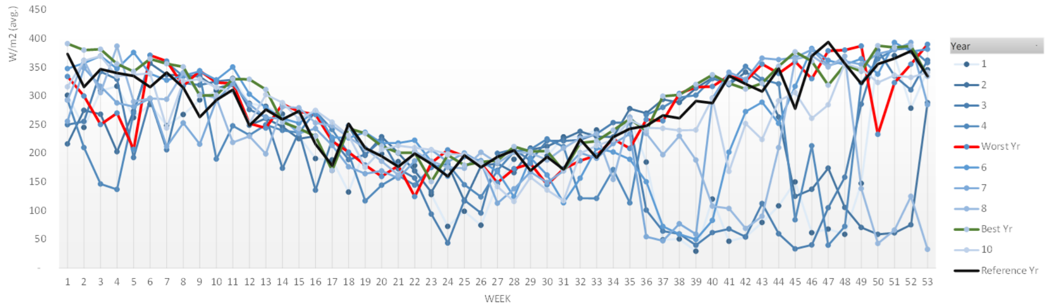
Wind and solar data for the off-grid and grid-connected Chilean mine are presented in this section.

B.1.1 *Atacama, Chile: Solar data for adequacy analysis*

Table B.1: Atacama, Chile: Summary of solar data

Years	Sum of Global Horizontal (kWh/m2)	Minimum Available Insolation over 1 day (%)	Minimum Available Insolation over 3 days (%)	Minimum Available Insolation over 7 days (%)	Average Minimum Available Insolation over 1/3/7 days (%)
1	1704	9%	9%	10%	9%
2	1987	9%	9%	13%	11%
3	1702	9%	9%	9%	9%
4	2023	9%	10%	11%	10%
Worst Yr	2325	12%	30%	61%	34%
6	2217	10%	10%	13%	11%
7	2139	9%	9%	13%	11%
8	1965	9%	10%	10%	10%
Best Yr	2498	23%	49%	71%	48%
10	2253	15%	33%	46%	31%
Reference Yr	2364	21%	46%	76%	48%
NASA-SSE (22 years of data)	2296	19%	44%	65%	43%

Figure B.1: Atacama, Chile: Weekly average insolation over 10 years

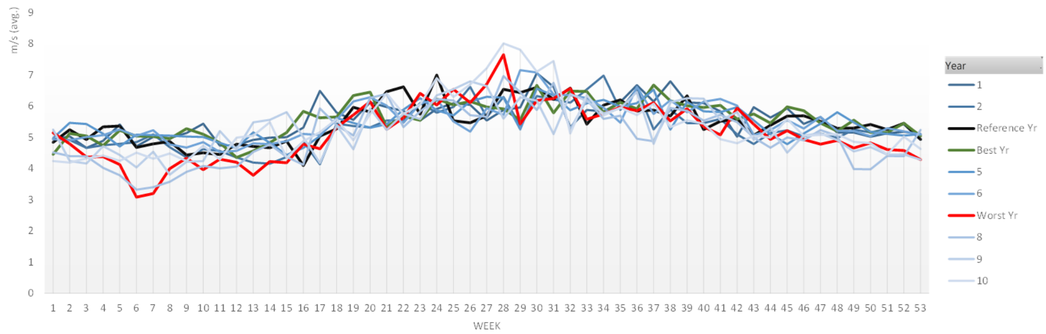


B.1.2 *Atacama, Chile: Wind data for adequacy analysis*

Table B.2: Atacama, Chile: Summary of wind data

Years	Mean Wind Speed (m/s)	Nb of hours above 5 m/s	Minimum nb of hours above 5 m/s over 1 day	Minimum nb of hours above 5 m/s over 3 days	Minimum nb of hours above 5 m/s over 7 days
1	5.58	4497	6	22	56
2	5.30	4205	6	20	48
Reference Yr	5.48	4324	0	18	47
Best Yr	5.59	4531	6	21	57
5	5.48	4341	5	21	51
6	5.53	4339	4	21	52
Worst Yr	5.16	4264	0	2	11
8	5.05	4158	0	0	23
9	5.27	4561	2	17	48
10	5.40	4526	0	17	48
Average	5.38	4375	3	14	39

Figure B.2: Atacama, Chile: Weekly average wind speed over 10 years



B.2 YUKON, CANADA

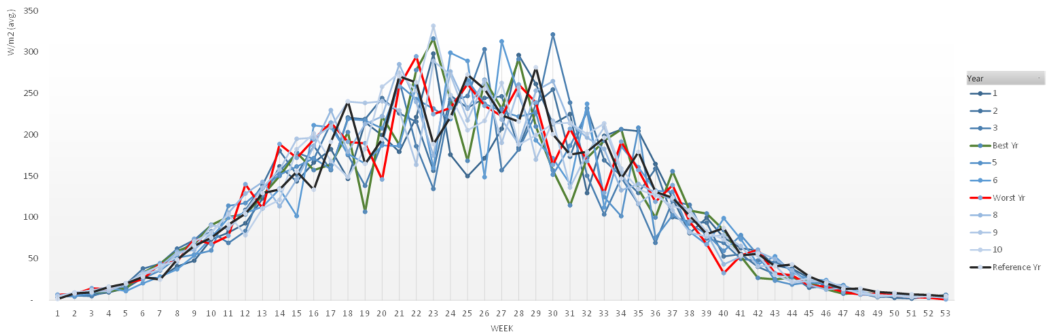
Wind and solar data for the off-grid Yukon mine are presented in this section.

B.2.1 *Yukon, Canada: Solar data for adequacy analysis*

Table B.3: Yukon, Canada: Summary of solar data

Years	Sum of Global Horizontal (kWh/m2)	Minimum Available Insolation over 1 day (%)	Minimum Available Insolation over 3 days (%)	Minimum Available Insolation over 7 days (%)	Average Minimum Available Insolation over 1/3/7 days (%)
1	964	16%	34%	59%	36%
2	986	29%	39%	61%	43%
Wost Yr	934	10%	27%	42%	26%
4	972	24%	59%	66%	50%
5	965	20%	41%	66%	42%
6	953	27%	48%	76%	50%
7	991	24%	59%	77%	54%
Best Yr	1012	37%	52%	78%	56%
9	1000	10%	40%	68%	39%
10	1000	21%	51%	66%	46%
Reference Yr	997	27%	52%	74%	51%
NASA-SSE (22 years of data)	1026	7%	30%	46%	27%

Figure B.3: Yukon, Canada: Weekly average insolation over 10 years

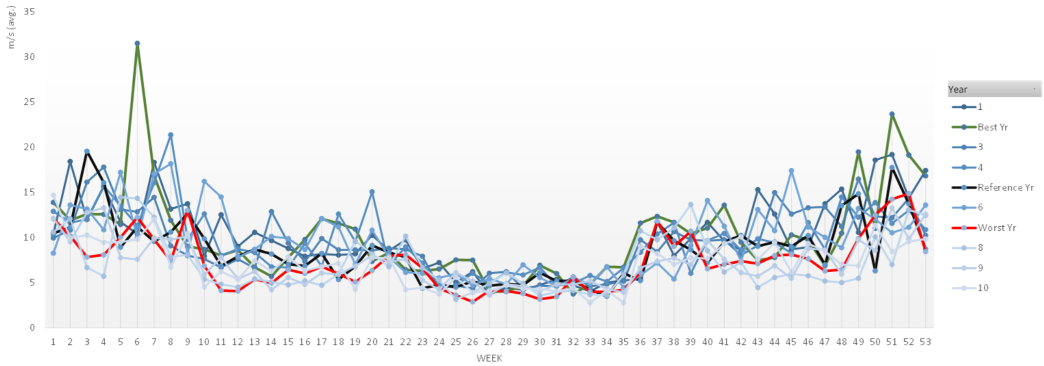


B.2.2 *Yukon, Canada: Wind data for adequacy analysis*

Table B.4: Yukon, Canada: Summary of wind data

Years	Mean Wind Speed (m/s)	Nb of hours above 5 m/s	Minimum nb of hours above 5 m/s over 1 day	Minimum nb of hours above 5 m/s over 3 days	Minimum nb of hours above 5 m/s over 7 days
1	9.98	6809	0	2	25
Best Yr	10.12	6902	0	5	31
3	9.37	6823	0	3	38
4	9.54	6927	0	0	36
Reference Yr	8.59	6386	0	0	18
6	9.65	6888	0	2	29
Worst Yr	7.18	5414	0	0	6
8	7.10	5412	0	0	12
9	7.13	5706	0	0	7
10	7.15	5933	0	0	9
Average	8.58	6320	0	1	21

Figure B.4: Yukon, Canada: Weekly average wind speed over 10 years



B.3 NORTH-WESTERN AUSTRALIA

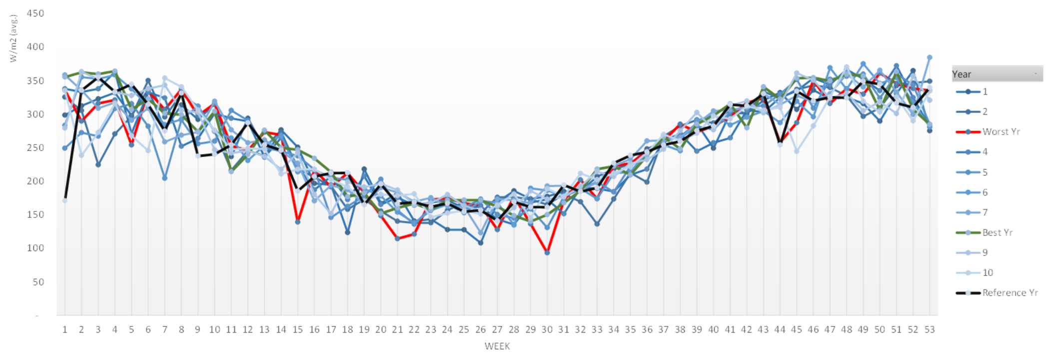
Wind and solar data for the off-grid Australian mine are presented in this section.

B.3.1 *North-Western Australia: Solar data for adequacy analysis*

Table B.5: North-Western Australia: Summary of solar data

Years	Sum of Global Horizontal (kWh/m2)	Minimum Available Insolation over 1 day (%)	Minimum Available Insolation over 3 days (%)	Minimum Available Insolation over 7 days (%)	Average Minimum Available Insolation over 1/3/7 days (%)
1	2192	16%	34%	59%	36%
2	2153	29%	39%	61%	43%
Wost Yr	2186	10%	27%	42%	26%
4	2212	24%	59%	66%	50%
5	2160	20%	41%	66%	42%
6	2223	27%	48%	76%	50%
7	2236	24%	59%	77%	54%
Best Yr	2255	37%	52%	78%	56%
9	2233	10%	40%	68%	39%
10	2158	21%	51%	66%	46%
Reference Yr	2205	27%	52%	74%	51%
NASA-SSE (22 years of data)	2212	10%	21%	43%	25%

Figure B.5: North-Western Australia: Weekly average insolation over 10 years

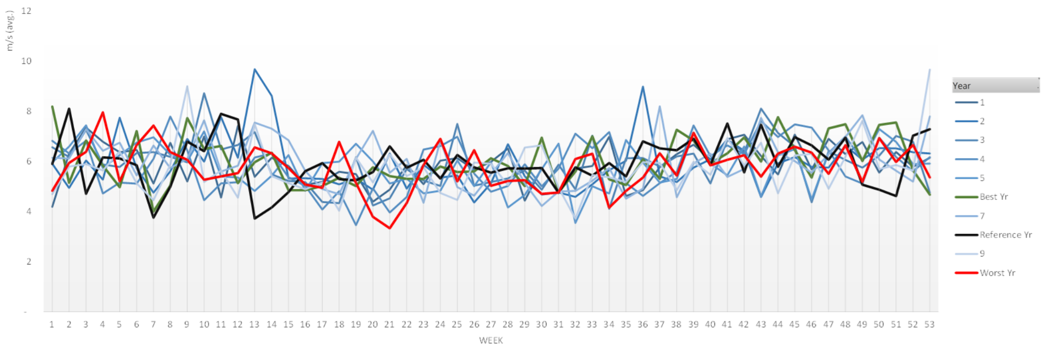


B.3.2 *North-Western Australia: Wind data for adequacy analysis*

Table B.6: North-Western Australia: Summary of wind data

Years	Mean Wind Speed (m/s)	Nb of hours above 5 m/s	Minimum nb of hours above 5 m/s over 1 day	Minimum nb of hours above 5 m/s over 3 days	Minimum nb of hours above 5 m/s over 7 days
1	5.93	5629	0	0	33
2	5.92	5461	0	0	27
3	5.95	5579	0	3	39
4	5.84	5396	0	0	14
5	5.82	5401	0	0	11
Best Yr	5.96	5707	0	2	33
7	5.98	5661	0	3	19
Reference Yr	5.92	5510	0	0	24
9	5.69	5070	0	0	20
Worst Yr	5.77	5335	0	0	10
Average	5.88	5475	0	1	23

Figure B.6: North-Western Australia: Weekly average wind speed over 10 years



C

FUEL PRICE FORECASTING

This appendix contains additional price forecasting data that have been used in the portfolio analysis in chapter 7 on page 181. Specifically, a range of future forecasted prices is first given on a plot with the expected mean as well as the uncertainty bands for each time period - based on the methodology given in 7.2.1 on page 185. Additional figures are subsequently provided for the Monte Carlo simulation of levelised fuel prices for each mine - colour coding: red for Atacama, Chile, blue for Yukon, Canada, and green for North-Western Australia.

C.1 DIESEL PRICE FORECASTING

Figure C.1: Diesel fuel prices: Forecast of future fuel prices (Yukon, Canada)

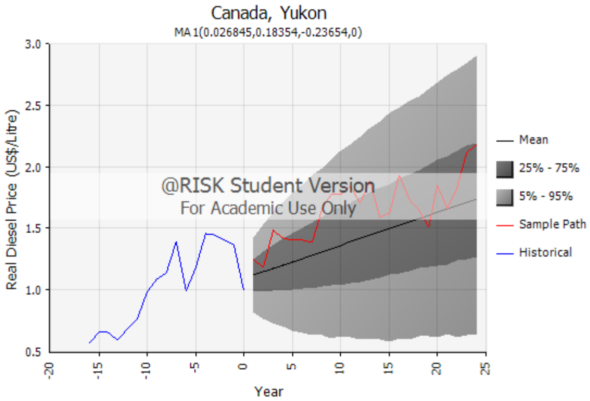
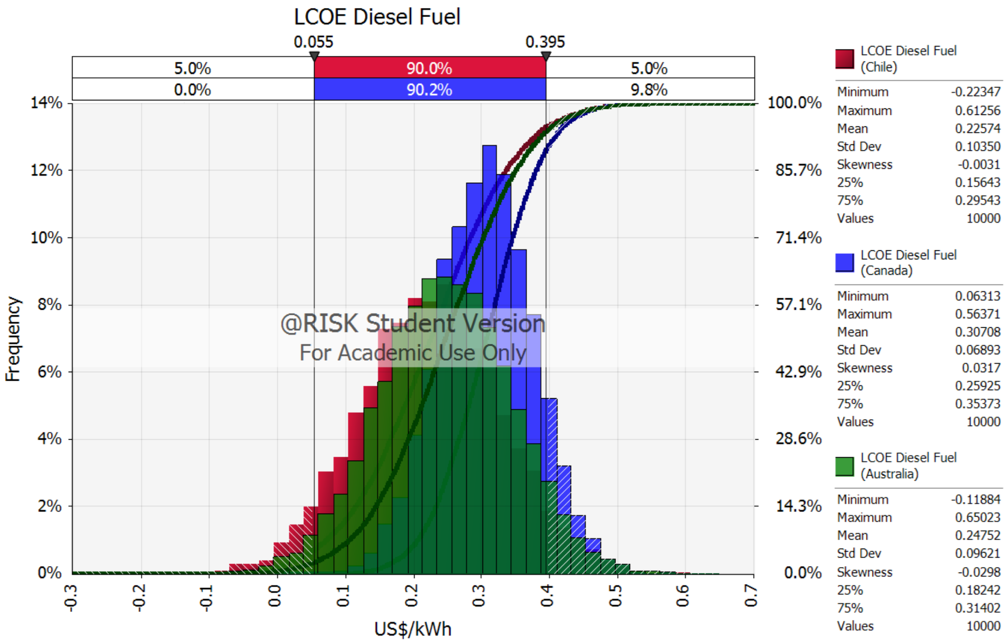


Figure C.2: Diesel prices: Monte Carlo analysis and statistical indicators



C.2 GRID POWER PRICE FORECASTING

Figure C.3: Grid marginal power prices: Forecast of future power prices (Atacama, Chile)

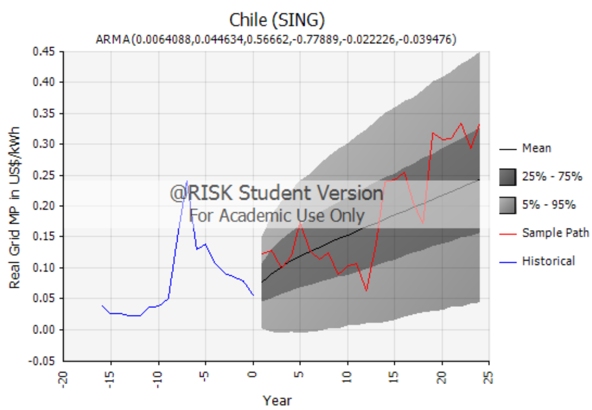
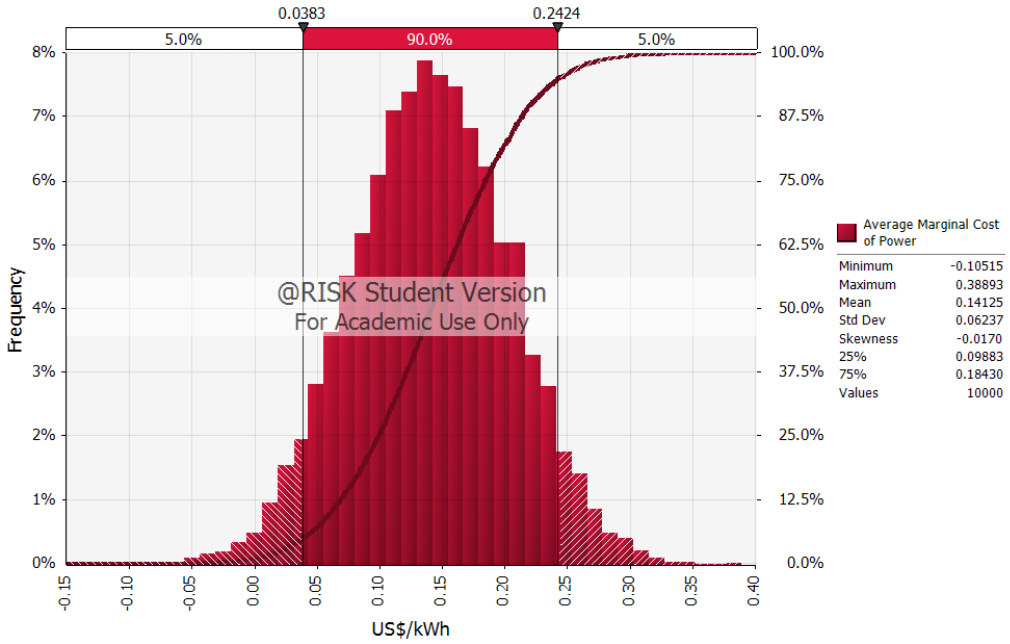


Figure C.4: Grid marginal power prices: Monte Carlo analysis and statistical indicators



C.3 LNG PRICE FORECASTING

Figure C.5: LNG fuel prices: Forecast of future fuel prices (Atacama, Chile)

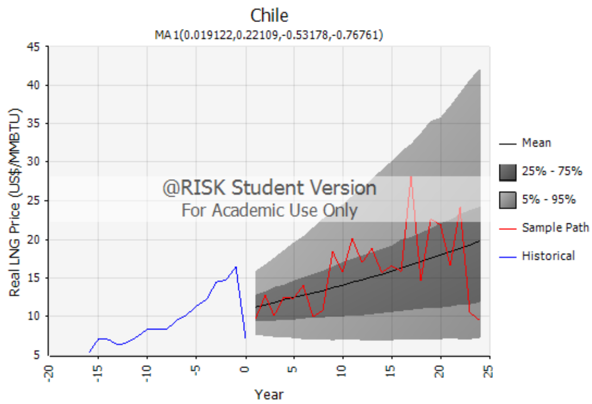


Figure C.6: CSP gas-backup with LNG fuel: Monte Carlo analysis and statistical indicators

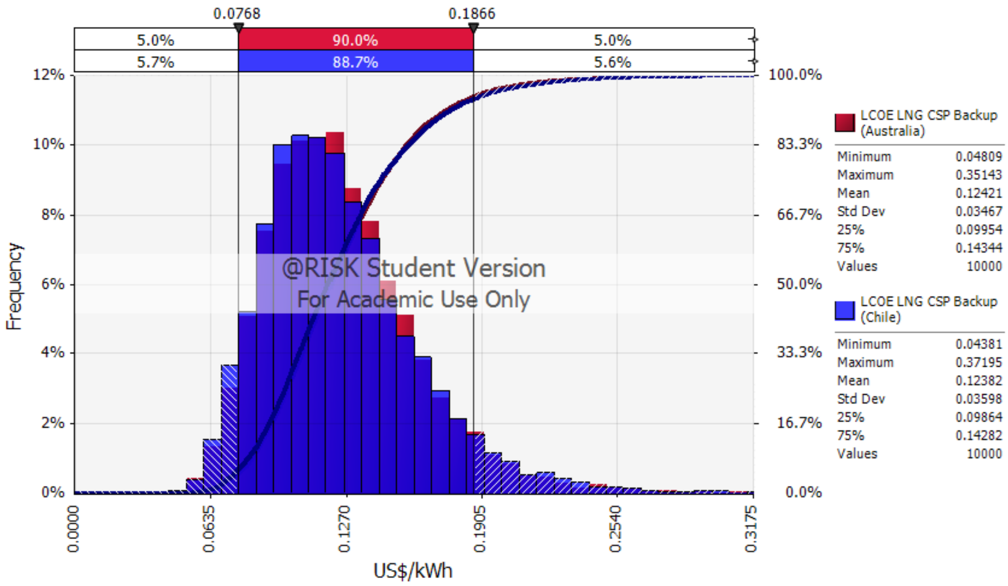
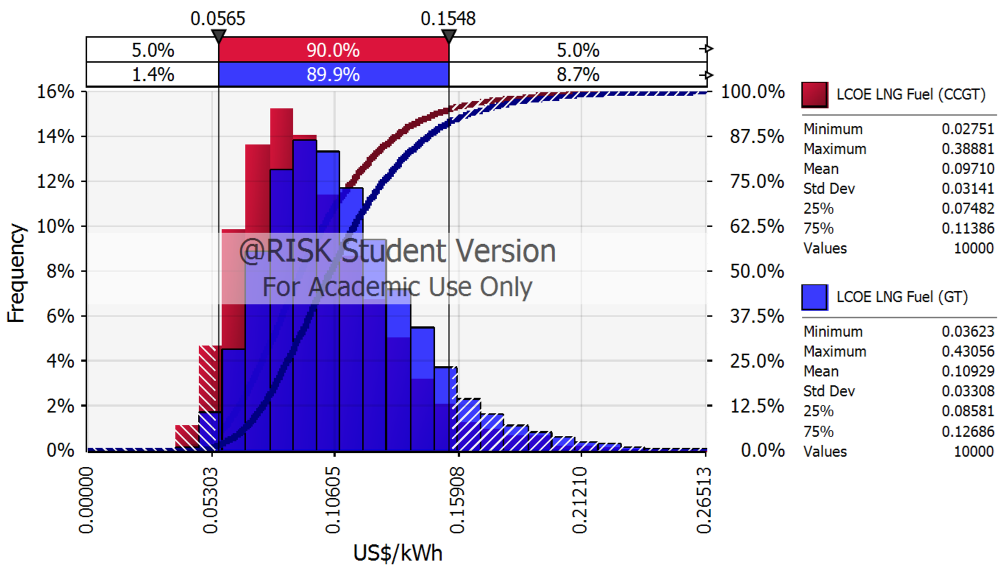


Figure C.7: CCGT / GT with LNG fuel: Monte Carlo analysis and statistical indicators (Yukon, Canada)



D

REVIEW OF ENERGY MODELS

In this section, a review of existing model is provided along with a discussion on the implications associated with the use of particular models.

To begin with, it is important to emphasise that a number of limitations are shared by all models. First, a model is always a simplification of the reality. In this sense, any given model tends to only capture the aspects that are deemed relevant but may not capture other important aspects (e.g. technological details, macroeconomic impacts). Second, all models rely on large amounts of data and a variety of parameters. The definition of these parameters can lead to great variation in results, and serious doubts can arise about the actual value of these parameters. Performing sensitivity analyses is therefore required to study the uncertainty surrounding the key model parameters. Third, assumptions about future technologies and demand have to be made for models with medium to short term focus. Those are inherently uncertain and cannot be estimated with precision. As a result, modelling results have to be treated with caution - with consideration for methodological completeness and data quality (Grubb et al., 1993).

D.1 MODELLING APPROACHES

The field of energy economics modelling is composed of two distinct approaches: technology oriented models known as bottom-up, and money-denominated macroeconomic models called top-down. While the former genre of economic model requires complex technological details (i.e. technological explicitness), the latter genre is generally constrained to economic inputs and outputs. Whereas countless models have been developed in the field of energy economics, there is a limited number of purposes considered in these models. Among others, they can be applied for characterizing the optimum technologies available in the context of regulatory planning, or evaluating environmental issues at a global scale. Generally, there are less technological details in global or large-scale models but potentially more technological options. Yet, most models take into consideration basic technological parameters such as technology, fuel, efficiency, fixed and variable costs, and lately greenhouse gases (Greening and Bataille, 2009).

More specifically, top-down models evaluate energy systems based on aggregate economic variables while bottom-up models are built based on disaggregated demand functions. Critics of the top-down approach emphasise that aggregate models cannot capture the complexity and the details associated with demand and supply. Yet, top-down approaches provide a number of advantages over bottom-up. For instance, top-down models can take into consideration the macroeconomic impacts and feedback relationships on a national or global scale. As such, this approach does not usually capture great details on technological characteristics but rather focuses on a broad equilibrium framework (Nakata, 2004). Table D.1 provides further limitations and advantages for each approach.

Table D.1: Pros and cons of top-down and bottom-up approaches (Nakata, 2004; Grubb et al., 1993)

	Pros	Cons
Top-down	• Can efficiently model the elasticity and substitutability among inputs • Tend to be more reliable for national or global scale over long runs • Include great details on macroeconomic parameters (e.g. employment, multiplier effects)	• Little details on sectorial characteristics • Low-level consideration of complexity between supply and demand • Basic modelling of technological parameters; Typically deterministic • Tend to underestimate the potential for low-cost efficiency improvements
Bottom-up	• Include extensive engineering details • Can easily capture the stochastic behaviour of a variety of model parameters • Provide more accurate information for targeted energy policies (i.e. sectorial, technology-based)	• Hidden costs and market barriers are typically ignored • Market imperfections and barriers to take-up are not explicitly considered • Little consideration for macroeconomic parameters (e.g. employment, GNP) • Tend to be less reliable for large-scale modelling over the long run

Another key distinction associated with energy models is the timescale. This is particularly important because different economic processes are operating on different timescales. On the one hand, short-term models (typically less than 5 years) focus on transitional effects and disequilibrium effects such as market responses, unemployment, and inflation. On the other hand, medium-term models (between 3 and 15 years) and long term models (more than 10 years) tend to take the hypothesis of a market equilibrium where all resources are completely allocated (Grubb et al., 1993). As a result, top-down models can be classified with two different types: either short-run macro-economic models or long-run resource allocation models. Yet, none of these distinctions are relevant for bottom-up models. In those models, the timescale is usually associated with the economic lifetime of the selected technologies in order to simulate and optimise resource allocation within model's constrains and objectives.

A bottom-up model is chosen in this research for two major reasons. First, the consideration of hybrid renewable systems implies to combine different intermittent technologies (e.g. wind, solar) in a single system along with dispatchable alternatives (e.g. storage, diesel). Subsequently, a bottom-up approach is favoured in order to take into consideration the engineering complexity of such system - each technology has to be sized in relation to all other technologies. Second, a number of different climate scenarios will be tested in the second research question, which implies that the model has to be able to account for different levels of intermittency. By contrast, this research does not intend to provide aggregated macroeconomic results but rather disaggregated technology-explicit results. In turn, a review of bottom-up optimisation models is provided as follows.

D.2 Review of existing modelling tools

Adequate modelling tools are critical means to support the research work of this PhD. Relevant tools for this research must be capable of considering the key concepts of the PhD - as proposed in the methodology and research questions. As a result, a number of models have been selected and reviewed in this section. Subsequently, this review focuses on the modelling tools that are related to the system design and optimisation of distributed and islanded energy systems. Further review of existing modelling tools is provided by Connolly et al. (2010); Manfren et al. (2011).

Based on initial analyses and past literature, it was determined that the optimal design of hybrid renewable power systems is a process that can be subdivided into six stages:

1. Simulation of power demand and modelling of selected energy systems (based on collected data or modelled data)

2. Definition of energy, economic and emission parameters and constraints (with regard to technological details and relevant contextual parameters)
3. Simulation of climate resources and consideration of different patterns of intermittency
4. Assessment of power reliability for security and adequacy issues (including value of lost load)
5. Simulation of system portfolio with regard to cost risk and mean system cost
6. System optimisation to least cost, least value of lost load, and least cost-risk

As a result, the relevant models for this research should include those capabilities in order to generate adequate results. Therefore, a number of existing modelling tools focusing on the analysis and optimisation of distributed energy systems have been identified in this section (Manfren et al., 2011), including: EnergyPLAN, DER-CAM, DEECO, EnergyPRO, H2RES, HOMER, COMPOSE, HYDROGEMS, TRNSYS, RETScreen, and SimRen. It is also important to mention that several additional tools were dismissed from this review because their focus was on policy analysis (e.g. XEONA, LEAP) or country-scale analysis (e.g. IKARUS, INFORSE). The "pure engineering" models were not considered due to their limited capabilities for economic optimisation (e.g. ETAP). A number of additional tools that focus on power reliability (e.g. Goel and Gupta (1997)) were also dismissed due to their lack of consideration of economic issues.

In turn, a review of the capabilities associated with selected energy models is provided.

D.2.1 *EnergyPLAN*

EneryPlan has been developed by Aalborg University in Denmark (Lund and Münster, 2003). The main purpose of the model is to simulate and optimise regional and national energy systems. Past research based on EnergyPLAN include the assessment of fuel cells for future energy systems (Mathiesen, 2008) and the implementation of 100% renewable on the island of MIjet in Croatia (Lund et al., 2007). While this tool is able to model disaggregated energy demand and simulate climate resources, it is limited by its deterministic input/output framework. Furthermore, EnergyPLAN is focused on the optimisation of system operations and not on the optimisation of system costs.

D.2.2 *DER-CAM*

DER-CAM (Distributed Energy Resources Customer Adoption Model) is a economic model for analysing the adoption of distributed energy systems. It has been in development at Berkeley Lab since 2000 (Firestone, 2004). Previous research based on DER-CAM include the assessment of small power-generation installations in the San Diego area (Edwards et al., 2002) and the examination of the effects of carbon tax on micro-grids using combined heat and power (Siddiqui et al., 2005). This tool suffers from a number of limitations, including: no deterioration of output or efficiency, no consideration for economies of scale and power reliability issues.

D.2.3 *DEECO*

The Unix program DEECO was developed by Bruckner et al. (2003) in order to simulate and optimise energy, emissions and costs based on input/output engineering relationships. Past papers based on DEECO include the high-resolution modelling of distributed energy resources for policy planning purposes (Morrison and Bruckner, 2002) and a small-scale analysis on competition and synergy between energy technologies for the city of Wurzburg, Germany (Bruckner et al., 1997). The main limitation of DEECO for this research is its deterministic approach - which therefore limits its ability to accurately incorporate probabilistic distributions.

D.2.4 *EnergyPRO*

EnergyPRO is an extensive modelling package for techno-economic and optimisation of energy systems. This software is developed and maintained by the company EMD International in Denmark. Previous studies based on EnergyPro include the optimal sizing of CHP and thermal storage under spot market conditions (Streckiene et al., 2010) and a simulation of compressed air energy storage for selling energy on the spot market with ToU prices (Lund et al., 2009). While this tool can be used to model islanded power systems, the main focus is on heat and power and residential energy demand. The tool is deterministic and does not account for probabilistic assessment of intermittency and fuel prices. Furthermore, this modelling package is sold for more than £3000 (price varies depending on modules) to energy modellers.

D.2.5 *H_2RES*

H_2RES is a tool that focuses on balancing the integration of renewable energy sources into energy-systems. It was developed in 2000 by the Instituto Superior Tecnico in Lisbon, Portugal and the University Of Zagreb, Croatia (Lerer et al., 2007). H_2RES was designed to increase the share of renewable sources into islanded energy systems. Previous studies conducted under H_2RES include the implementation of hydrogen into island energy systems (Krajačić et al., 2008) and the integration of 100% renewables into the island of MIjet in Malta (Krajačić et al., 2009). Whereas this tool is one of the most specialised tool for off-grid systems, it suffers from the lack of consideration of system costs and reliability issues. Hence this tool is not suitable for an economic analysis where system costs and reliability are of primary interest.

D.2.6 *HOMER*

HOMER is a techno-economic modelling tool for islanded systems. It has been developed by the National Renewable Energy Laboratory in the USA since 1992 (Lilienthal et al., 2005). Past publications based on HOMER includes an assessment of the feasibility to implement a stand-alone wind-diesel hybrid in Saudi Arabia (Rehman et al., 2007) and the simulation of a hybrid hydrogen stand-alone system in Newfoundland, Canada (Khan and Iqbal, 2005). In contrast to other tools, HOMER takes into consideration the economics of a project by minimising the total discounted costs. Another interesting capability of HOMER is the possibility to run sensitivity analyses on key parameters of the model (i.e. the user can assess the impact of price variations on total system costs). The model HOMER suffers from its deterministic approach, the lack of consideration of the value of lost load, and the inability to compare the cost risks of different energy alternatives.

D.2.7 *COMPOSE*

COMPOSE is a techno-economic model developed in a PhD thesis at Aalborg University, Denmark (Blarke, 2008). The aim of the model is to assess the feasibility of implementing intermittent sources in energy projects. It has been used to analyse the integration of heat pumps with CHP plants and to assess the benefits of energy storage in renewable energy systems (Blarke and Lund, 2008). In contrast to other modelling tools, COMPOSE is particularly interesting for taking into consideration uncertainty parameters. Specifically, it allows the user to perform a Monte Carlo analysis as well as extensive risk analyses. Import of data from EnergyPRO and RETScreen are also allowed in COMPOSE. However, the model seems to have received little attention since its development (i.e. no recent publication under COMPOSE). Technical limitations of COMPOSE include the lack of consideration of storage losses and variable fuel efficiency. Furthermore, the economic parameters associated with reliability analyses and portfolio modelling are not considered in the system optimisation.

D.2.8 *HYDROGEMS*

HYDROGEMS is a simulation tool suitable for analysing the performance of energy systems including hydrogen and renewable sources. It was developed at the Institute for Energy Technology (Norway) as part of a PhD research (Ulleberg, 1998), and was integrated into TRNSYS in 2006. Specific research conducted under HYDROGEMS include the simulation of stand-alone PV-hydrogen (Zoulias et al., 2006) and wind-hydrogen systems (Ulleberg et al., 2010). The main objective of the model is to simulate hydrogen mass flows, electrical generation, and electrical usage. While capital and operation costs are considered in HYDROGEMS, the model does not integrate cost optimisation capabilities - only a cost comparison of different system alternatives.

D.2.9 *TRNSYS*

TRNSYS is a modelling program that focus on the assessment of single-projects and islanded energy systems. It is built with an open source code that simulates the electricity and heat sectors of an energy system. TRNSYS has be used in previous research for modelling hybrid PV-thermal energy systems in Cyprus (Kalogirou, 2001) as well as the design of solar-thermal system prototype (Souliotis et al., 2009). The tool has a design emphasis on system simulation and therefore do not consider cost optimisation. Yet, system costs can be analysed and compared in an external spreadsheet tool. Finally, the model TRNSYS is sold for £1500+ to academics and £3000+ to commercial users.

D.2.10 *RETScreen*

The RETScreen Clean Energy Project Analysis Software has been developed by Natural Resources Canada in order to provide guidance to governments, utilities, and academics in their decision-making (Leng et al., 2004). Examples of previous work under RETScreen include the feasibility assessment of a solar PV project in Egypt (El-Shimy, 2009), and a wind farm development in Algeria (Himri et al., 2009). In contrast to other optimisation tools, RETScreen is based on a cost comparison between a base scenario and other potential system alternatives. It includes a number of economic indicators such as the net present value and the internal rate of return. Interestingly, RETScreen is one of the unique modelling tool that offers extensive capabilities for sensitivity analysis and risk assessment (e.g. Monte Carlo). Yet, the RETScreen model remains a simulation tool and therefore does not intend to optimise system size, system configuration, and total costs. A further limitation of RETScreen is its low resolution based on annual averages of power demand and supply.

D.2.11 *SimRen*

SimRen is a bottom-up modelling tool developed by the Institute for Sustainable Solutions and Innovations in Germany (Peter et al., 2009). This simulation package is based on detailed modelling of energy demand, energy management, and energy supply - with a strong focus on the implementation of renewable sources. It was previously used to model a 100% renewable energy system for Japan (Lehmann, 2003) and the implementation of 100% renewable power generation for the region of Catalonia in Spain (Peter et al., 2009). SimRen is strongly focused on system simulation and does not currently take into consideration the system costs.

D.3 SUITABILITY OF EXISTING MODELS

Based on this review of models, it appears that several required capabilities for this research are missing or incomplete in existing models (see table D.1 on page 315 for a comparison of model capabilities). Overall, the strengths and weaknesses associated with existing models of distributed and islanded energy systems can be summarised as follow:

- Most existing models for distributed systems are focused on regional or national power systems - yet, they all seem to be capable of modelling islanded energy systems.
- Only two models have been specifically developed to assess islanded energy systems (i.e. H_2RES, HOMER), and only one focuses on cost optimisation (i.e. HOMER).
- Most models are capable of considering solar and wind energy technologies, but only a few models (i.e. RETScreen, SimRen) include the most complex alternatives (e.g. thermal storage).
- Energy storage technologies are typically considered for battery and fuel cell energy storage. Pumped hydro energy storage is included in EnergyPRO, COMPOSE, and SimRen.
- Most of the models focusing on system simulation are based on high resolution time steps (between 0.01 sec to 15 min.) while models focusing on cost optimisation tend to be based on hourly data.
- A majority of models uses a one or two year scale, which is then extrapolated to the following operation years (e.g. HOMER uses a maximum of two years while SimRen and DER-CAM are based on a one year time-frame).
- On the uncertainty side, few models offer stochastic capabilities to measure the uncertainty associated with power outages (i.e. DER-CAM) and input parameters (i.e. COMPOSE, RETScreen).
- None of the reviewed models are capable of considering the value of lost load in the optimisation of energy systems - hence neglecting reliability costs.
- Reviewed models focusing on system simulation are typically not capable of optimising system costs (i.e. EnergyPLAN, HYDROGEMS, TRNSYS, RETScreen, and SimRen) but instead provide a cost comparison between different system alternatives.
- Three models offer built-in sensitivity analyses on input parameters (i.e. HOMER, COMPOSE, RETScreen) - while analysis must be done by changing input parameters in other models.

In this research, the following modelling capabilities are sought: system simulation of islanded systems, renewable and storage integration (e.g. wind, solar, molten salt storage), stochastic capabilities, cost analysis, and system portfolio modelling. As shown in table D.1, such capabilities are not present in existing modelling tools. For instance, it appears that not one of the existing models is currently capable to consider the value of lost load, the cost risk (from a portfolio theory perspective), and energy security issues. This technological and methodological incompleteness could potentially lead to misleading results for mining stakeholders.

As a result, this research will be based on a modelling tool developed by the author. This new research tool named HELiOS- Mining ("Hybrid Energy Load Optimisation System for the Mining Industry") will take into consideration the additional analyses that are required for this thesis including: detailed technological characteristics (e.g. part-load efficiency, storage losses), reliability costs, and probabilistic analysis of cost risks.

Figure D.1: Comparison of existing bottom-up modelling tools for distributed / islanded energy systems

Model name	Main focus	Integration of renewables and energy storage	Typical time step	Uncertainty	Static / Dynamic	Reliability analysis	Objectives of optimisation	Sensitivity analysis
EnergyPLAN	National and local projects	Wind, solar, tidal, hydro, electricity storage, hydrogen storage	1 hour	Deterministic	Dynamic demand, supply and power prices	Adequacy *(analytical system sizing)*	Simulation of system operation, system costs are compared for each system alternative	No built-in functions
DER-CAM	Local / Single project	Solar, fuel cells	15 min.	Deterministic (stochastic module for fuel cell outages)	Dynamic demand, supply and power prices	Adequacy *(analytical system sizing),* Security analysis on fuel cells	Investment costs and carbon emissions *(based on MILP algorithm)*	No built-in functions
DEECO	National and local projects	Solar, wind, thermal storage, super-conducting storage	1 hour	Deterministic	Dynamic demand, supply and power prices	Adequacy *(analytical system sizing)*	Investment costs *(based on MILP algorithm)*	No built-in functions
EnergyPRO	Local / Single project	Solar, wind, thermal storage, electricity storage, pumped-hydro energy storage	1 hour	Deterministic	Dynamic demand, supply and power prices	Adequacy *(analytical system sizing)*	Investment costs	No built-in functions
H2RES *(RenewIsland methodology)*	Islanded systems	Solar, hydro, geothermal, hydrogen storage, hydro storage and battery storage	1 hour	Deterministic	Dynamic demand, supply and power prices	Adequacy *(analytical system sizing)*	Maximum renewable	No built-in functions
HOMER	Islanded systems	Solar, wind, hydro, biomass, fuel cells, batteries, hydrogen	1 min.	Deterministic	Dynamic demand, supply and power prices	Adequacy *(analytical system sizing)*	Investment costs *(linear algorithm)*	'What-if' analysis on all key variables
COMPOSE	Local / Single project	Solar, wind, thermal storage, electricity storage, pumped-hydro energy storage	1 hour	Stochastic (Monte Carlo)	Dynamic demand, supply and power prices	Adequacy *(analytical system sizing)*	Investment costs	Monte Carlo analysis on input parameters
HYDROGEMS	Local / Islanded systems	Solar, wind, hydrogen, fuel cells	1 min.	Deterministic	Dynamic demand, supply and power prices	Adequacy *(analytical system sizing)*	Simulation of system operation *(system costs are compared for each system alternative)*	No built-in functions
TRNSYS	Local / Islanded systems	Solar, wind, battery storage	0.01 sec. to 1 hour	Deterministic	Dynamic demand, supply and power prices	Adequacy *(analytical system sizing)*	Simulation of system operation *(system costs are compared for each system alternative)*	No built-in functions
RETScreen	Local / Single project	Solar, wind, hydro, tidal, ocean thermal and current power, fuel cells	Monthly / Annual averages	Stochastic (Monte Carlo)	Static demand, power supply, and power prices	Not included	Simulation of system operation (*costs are compared against a base scenario)*	Monte Carlo analysis on input parameters
SimRen	National and local projects	Solar, wind, hydro, geothermal, biomass, pumped hydro , batteries, hydrogen storage	15 min.	Deterministic	Dynamic demand, supply and power prices	Adequacy *(analytical system sizing)*	Simulation of system operation *(no consideration for costs)*	No built-in functions