PONTIFICIA UNIVERSIDAD CATOLICA DE CHILE

SCHOOL OF ENGINEERING

THE PARADIGM SHIFT FOR RESIDENTIAL END-USERS OF ELECTRICITY DUE TO RENEWABLE ENERGY PENETRATION

CRISTIAN PABLO BUSTOS SÖLCH

Thesis submitted to the Office of Graduate Studies in partial fulfillment of the requirements for the Degree of Doctor in Engineering Sciences

Advisor:
DAVID WATTS

Santiago de Chile, July 2017

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Members of the Committee:

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HUGH RUDNICK

CARLOS SILVA

MATÍAS NEGRETE-PINCETIC

ALBERTO LAMADRID

JORGE VÁSQUEZ

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To my son and wife, who have always been by my side and have never stopped believing in me.

ACKNOWLEDGMENT

First and foremost, I want to thank my dear wife and son for always being by my side, supporting me in the most difficult of times, even when I failed to believe in myself. I am especially thankful of my wife, Paula, who had the patience of witnessing these long years' madness, which have resulted in this document I hope can be helpful to anyone. I also want to thank my dear son, Sebastián, who is the "*sun of my life*" and who was born seeing his father submerged in ISI-papers. He somehow managed to enlighten me and transformed my family into my most important research-field and passion. To both of you, my most devoted love.

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PONTIFICIA UNIVERSIDAD CATOLICA DE CHILE

ESCUELA DE INGENIERIA
DEPARTAMENTO DE INGENIERÍA ELÉCTRICA

EL CAMBIO DE PARADIGMA PARA USUARIOS RESIDENCIALES DE ELECTRICIDAD DEBIDO A LA PENETRACIÓN DE ENERGÍAS RENOVABLES.

Tesis enviada a la Dirección de Postgrado en cumplimiento parcial de los requisitos para el grado de Doctor en Ciencias de la Ingeniería.

CRISTIAN PABLO BUSTOS SÖLCH

Resumen

Todo el planeta podría beneficiarse del impresionante cambio de paradigma que los usuarios finales de la electricidad enfrentarán en el futuro. Este cambio está ocurriendo hoy principalmente en el mundo desarrollado debido a incentivos económicos a favor del medio ambiente, pero podría propagarse muy pronto a países en desarrollo cuando tales incentivos no sean necesarios. Drásticas reducciones en costos de las tecnologías asociadas a microrredes y a Recursos Energéticos Distribuidos (*DERs* por sus iniciales en inglés) permitirían este cambio en países con menos desarrollo, y permitirían la entrada de nuevos servicios que generarían beneficios adicionales para los usuarios finales conectados a la red. Además, estas reducciones de costos también podrían permitirles a comunidades aisladas el acceso a la electricidad, mejorando su calidad de vida. Relacionadas transversalmente a ambos usuarios finales, tanto conectados a la red como sin acceso, están las energías renovables. Para estas tecnologías, los avances en la predicción climática podrían reducir el riesgo percibido por quienes deciden instalar energías renovables. Teoría y práctica sugieren que en el mundo los sistemas fotovoltaicos (*PV*) seguirán siendo la tecnología limpia dominante para el usuario final, tecnología que se ha desplegado masivamente en Europa, Estados Unidos y más recientemente en Asia. Nuestra investigación reconoce vacíos claves en la literatura que pueden mermar las

posibilidades del usuario final en el futuro: 1) Las actuales metodologías no consideran adecuadamente la predictibilidad climática en términos financieros, ya que no reconocen que la variabilidad climática es parcialmente predecible y que, por lo tanto, esta componente predecible puede ser descontada del riesgo financiero de los proyectos de energías renovables. 2) Las metodologías actuales basadas en microrredes (μGs) optimizadas que le permiten obtener acceso a la electricidad a comunidades asiladas, no incorporan adecuadamente las necesidades y restricciones de estras comunidades, a pesar de haber 1.1 billones de personas sin acceso a la electricidad en el mundo y a pesar de que las microrredes podrían representar, en muchos casos, su mejor solución. 3) No existe una estimación cuantitativa del impacto que tienen diferentes diseños tarifarios bajo una regulación de facturación neta ("netbilling" en inglés) sobre los usuarios finales, la distribuidora y el regulador considerando la tendencia a la baja de los costos de los paneles *PV*, a pesar de que la penetración de *DERs* en las redes de distribución ya está afectando a millones de personas. Así, hacemos algunas contribuciones claves que habilitarían el cambio de paradigma en los usuarios finales: i) Proponemos una metodología para reducir el riesgo financiero de proyectos *PV* a través de la modelación de la componente predecible de la radiación solar usando 3 oscilaciones océano-atmosféricas. La metodología fue desarrollada para una planta *PV* de gran escala pero podría ser fácilmente extendida para techos *PV*, así como para hidroelectricidad, viento y otras energías renovables. ii) Proponemos una metodología que ofrece una gama de diseños de microrredes a comunidades aisladas para darles acceso a la electricidad, donde cada uno de estos diseños es óptimo para un consumo particular y un valor de carga perdida (*VOLL*). La comunidad deberá elegir el diseño que mejor se ajuste a sus necesidades. iii) Proponemos un marco conceptual robusto (de peor caso) para entender la decisión de cada usuario de invertir en *DERs* usando microrredes óptimas, cuantificando así el impacto de diferentes diseños tarifarios y distintas decisiones del regulador sobre los usuarios finales y las distribuidoras. Para todas las metodologías y marcos conceptuales se desarrollaron casos de estudio en Chile, aprovechando su impresionante recurso solar. Adicionalmente, se estudiaron 10 casos a lo largo de Chile que muestran que el riesgo financiero para *PV* podría estar siendo sobreestimado hasta la fecha. Los modelos climáticos para Chile muestran que el riesgo financiero mensual para *PV* puede ser reducido debido a la estacionalidad (entre un 81% a 96% de la varianza del margen). Una vez descontada esta estacionalidad, las oscilaciones océano-atmosféricas pueden reducir adicional el riesgo de 6% a 13%. Los resultados también muestran que es posible ofrecerles a comunidades aisladas un portafolio de suministro a través de un trade-off entre costo y cobertura de las necesidades eléctricas. Este trade-off estaría formado de distintos diseños de microrredes para comunidades aisladas. Finalmente, para la penetración de *DERs* en los sistemas de distribución con alto potencial solar (norte de Chile) se ratifica que la tecnología dominante debería ser la *PV* y que su despliegue comenzaría en un par de años con usuarios que generarían electricidad para su autoconsumo, Luego, después de algunos años más, los usuarios inyectarían parte de su generación a la red. El impacto sobre los usuarios y la distribuidora dependerá de las decisiones del regulador, pero las diferencias de costo entre usuarios dueños-de-*DERs* y no-dueños-de-*DERs* podrían eventualmente llegar a ser colosales. También las distribuidoras podrían enfrentar riesgos significativos de quiebra. El análisis presentado permitiría habilitar un mejor y más justo futuro para los usuarios finales, así como para varios otros actores, basado principalmente en energías renovables y limpias como la *PV*. Bajo este escenario, ¿cuál sería la solución óptima para un sistema que quiera integrar en el futuro redes aisladas a la red de distribución? ¿Cómo debe diseñarse su regulación integrada? Aún quedan muchas preguntas abiertas y mucho por investigar.

Miembros de la Comisión de Tesis Doctoral

DAVID WATTS

HUGH RUDNICK

CARLOS SILVA

MATÍAS NEGRETE-PINCETIC

ALBERTO LAMADRID

JORGE VÁSQUEZ

Santiago, Julio 2017

PONTIFICIA UNIVERSIDAD CATOLICA DE CHILE
SCHOOL OF ENGINEERING
DEPARTMENT OF ELECTRICAL ENGINEERING

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CRISTIAN PABLO BUSTOS SÖLCH

Abstract

The whole planet could benefit from the impressive paradigm shift that end-users of electricity may face in the future. This change is taking place today mainly in the developed world due to economic incentives in favor of the environment, but may soon spread into developing countries when those incentives become unnecessary. The drastic cost reductions of microgrids' technologies and of Distributed Energy Resources (*DERs*) could allow this change in less developed countries, and could allow the entrance of new services that could generate new benefits for grid-tied end-users. Even more, these cost reductions could allow access to electricity for isolated communities, improving their quality of life. Renewable energies are related to both grid-tied and isolated end-users. For these technologies, advances made in climate prediction could also reduce the perceived risk for those who decide to install renewable energies. Theory and practice suggest that photovoltaic systems (*PV*) will remain a dominant clean technology for end-users worldwide, having already been deployed massively in Europe, the USA and more recently in Asia. Throughout our research we recognize several key voids in the literature related to the future of end-users: 1) Current methodologies do not appropriately account for climate predictability in financial terms because they do not recognize that climate variability is partly predictable and that this predictable component can therefore be discounted from financial risk in renewable energy projects. 2) Today's methodologies, based on

optimized microgrids (μGs) that give isolated communities access to electricity, do not properly address communitys' needs and restrictions, despite the fact that 1.1 billion people do not have access to electricity and despite μG's potential to become their best solution. 3) No quantitative estimation exists of the impact of different tariff designs, under a netbilling regulation, on end-users, utilities and regulators considering downward sloping *PV* panel cost trends, and despite the fact that millions of people are already being affected by *DER* penetration. Thus, we make some key contributions that could shift end-users' electricity paradigm: i) We propose a methodology to reduce financial risk of *PV* projects through the modeling of predictable components of solar radiation and 3 ocean-atmospheric oscillations. The methodology was developed for a large-scale *PV* plant but could be easily extended for rooftop *PV*, as well as for hydro, wind and other renewable resources. ii) We propose a methodology that offers a range of microgrid designs to an isolated community, where each of them is optimal for a particular consumption pattern and value of lost load. The community will have to choose the one that best suits their needs. iii) We propose a robust framework (worst-case) to understand the decisions of end-users to install *DER* using optimal μGs, thus quantify the impact of different tariff designs and dissimilar regulatory decisions on end-users and utilities. For all methodologies and frameworks, case studies were conducted in Chile to take advantage of its outstanding solar potential. Additionally, 10 case studies conducted along Chile show that *PV*'s financial risk could have been overestimated by the industry so far. Climate models for Chile show that monthly financial risk for *PV* could be reduced due to the seasonality of solar radiation (81% to 96% of the variance of profit). Once this seasonality is discounted, ocean-atmospheric oscillations may push risk between 6% and 13% further down. Also, results show that it is possible to offer isolated communities a portfolio of supply options through a trade-off between cost and coverage of electricity needs. This trade-off would be built from different microgrid designs for isolated communities. Finally, results confirm for the penetration of *DER* in distribution systems with high solar radiation (north of Chile) that *PV* should be the dominant technology and that its deployment could begin in a few years for end-users' self-consumption followed (after some more years) by end-users' injection into the grid. The impact on end-users and utilities will depend on regulators' decisions but differences in cost between *DER*-owners and non-*DER*-owners could eventually become colossal. Also, utilities could face significant bankruptcy risk. The analysis presented could enable a brighter and fairer future for end-users and several other stockholders based mainly on clean renewable energies such as *PV*. What would be the optimal solution for a system that in the future would integrate these isolated grids into the distribution system? How should the integrated regulation be? A lot of questions are still open and there is still plenty to be researched.

Members of the Doctoral Thesis Committee:

DAVID WATTS

HUGH RUDNICK

CARLOS SILVA

MATÍAS NEGRETE-PINCETIC

ALBERTO LAMADRID

JORGE VÁSQUEZ

Santiago, July 2017

1 INTRODUCTION

1.1 Climate change: The key driver of change in the energy sector

"*Crisis brings opportunity and change*", says a Chinese proverb. This is what climate change has brought to us. From the moment the first voices began to talk about climate change until now a lot has changed. Social conscience has changed - as well as politics and markets. The energy sector is a remarkable example since its transformation due to climate change has not only been dramatic, but has also created unthinkable opportunities.

1.2 Change at the end-user level in distribution systems

At the end-user level, change in the energy sector has been mainly focused on the developed world, which has pushed the innovation of renewable energies mainly through incentives and subsidies, taking advantage of their larger budgets and responding to their responsibility as major Green House Gas (*GHG*) emitters. Here, thanks to those financial aids, a lot of Distributed Energy Resources (*DERs*) have emerged as potential technologies that could offer new services to the end-user while reducing – at least potentially – *GHG* emissions. To name a few, one can mention photovoltaic (*PV*) systems, Combined Heat and Power (*CHP*), Electric Vehicles (*EV*), microturbines, wind turbines and Distributed Energy Storage Systems (*DESS*).

1.2.1 Distribution systems' change: In developed countries due to environmental concerns and large budgets. In developing countries due to grid-parity reached in some early regions.

Millions of people are experiencing life-transforming changes in their electricity supply around the world. In the last few years electricity alone, end-users in developed countries (e.g., the USA and Europe) have been increasingly self-consuming electricity produced from their own green Distributed Energy Resources (*DERs*) and injecting their surplus into the grid, often using *PV* rooftops or small-scale wind generation ("California Solar Statistics," 2017, *Small Wind World Report*, 2015; Wirth & Schneider, 2017). These new users, sometimes referred to as prosumers, have also been choosing their electricity retailer from several options and have been assessing their own energy consumption with the use of smart-meters ("Choose Energy Acquires Power2Switch," 2013, "Compare The Best Texas Electricity Providers," 2017; Hunt, 2013; Yadack, Vermeulen, & Pyka, 2017).

These changes in the electricity arena are mainly driven by new environmentally friendly people and policies implemented mostly in developed countries,while being supported by technology development (Commission, 2016; European Commission, 2009; Wiser et al., 2016). In these countries, environmental concerns and budgets have usually been large and durable enough to incentivize both the market expansion of new technologies (e.g., *DER*) and the reduction of per-unit costs (e.g., through *learning-by-doing* or technology breakthroughs (Rubin, Azevedo, Jaramillo, & Yeh, 2015)). In addition, changes in the end-consumers' electricity supply have diminished their dependency on distribution systems, strongly impacting grids' expansion and remuneration. Although *DERs* and other technologies are not likely to be incentivized in developing countries due to low government budgets and other more urgent social priorities, *DERs* could be deployed massively if technology costs drop below grid-parity[1], which may already be happening in some places (e.g., Chile).

1.2.2 Impact of a high penetration of *DERs* and tariff design on distribution system's customers, utilities and regulators.

Considering current regulation, massive deployment of *DERs* could heavily increase distribution system charges to customers because distribution companies' (discos') revenues - in a large proportion - come from selling electricity at a volumetric per unit energy charge that bundles generation costs and network tariffs. That is, the total investment, *O&M* and administration cost of the distribution system would have to be paid for by less consumed electricity units if a large number of customers would install their own *DER,* thus increasing grid's per-unit-energy-charges. If authorities do not allow for utilities to raise charges (e.g., because utilities' remuneration processes do not endogenize *DERs* penetration) or if *DERs* penetration develops too fast and authorities are not capable of reacting in time (e.g., because of a rigid regulation), distribution companies would be put at a higher bankruptcy risk (i.e., increasing the probability of not recovering their costs). Conversely, if the utility is allowed to raise their tariffs in synchrony with *DER*'s deployment, the utility-

[1] Grid parity is referred to as the moment when the generation cost of a technology that includes all its components (i.e., investment, *O&M*, among others) becomes lower than the cost of the conventional source of electricity supply of the grid.

revenue-problem would be solved. Nevertheless, if tariffs rise, end-users would be encouraged to deploy *DER* even further, which in turn may increase tariffs again. This cycle is called in literature the distribution system *Death Spiral* (*DS*) (I. P. Arriaga, Knittel, & Lester, 2014; Sioshansi, 2016), which is a positively reinforcing loop that could eventually be unsustainable, possibly ending with the end-user disconnecting form the distribution grid.

1.2.3 World's deployment of *PV*: the dominant technology at the end-user level

Of all *DER*-technologies, the one that has been most massively deployed around the world at the end-user level is - without a doubt - *PV*. In recent years, photovoltaics (*PV*) have strongly penetrated the international energy markets at exponential growth rates, mainly driven by subsidies (Chilean Energy Ministry, 2008; "Chilean Renewable Energy Law (Modification)," 2013; European Commission, 2009, 2015; Heeter & Bird, 2013; McGinn et al., 2013; Pica Téllez, Sauma Santis, Valdés Rojas, & Pérez Valenzuela, 2015) and by strong and sustained reductions of *PV* cell costs (Mints, 2014; Swanson, 2006). Europe led the installation of capacity until 2011. Since then, incentives were reduced in Europe and the market shifted to China, Japan and the USA (see Figure 1-1). In 2014, China was the main installer with 10.6 GW of the 40 *GW* installed that year. Next in relevance was Japan with 9.7 *GW*, Europe with 7 *GW* and the USA with 6.5 *GW*. However, all these markets sustained their growth (and explained their falls) due to subsidies and supporting policies (Rekinger, Thies, Masson, & Orlandi, 2015).

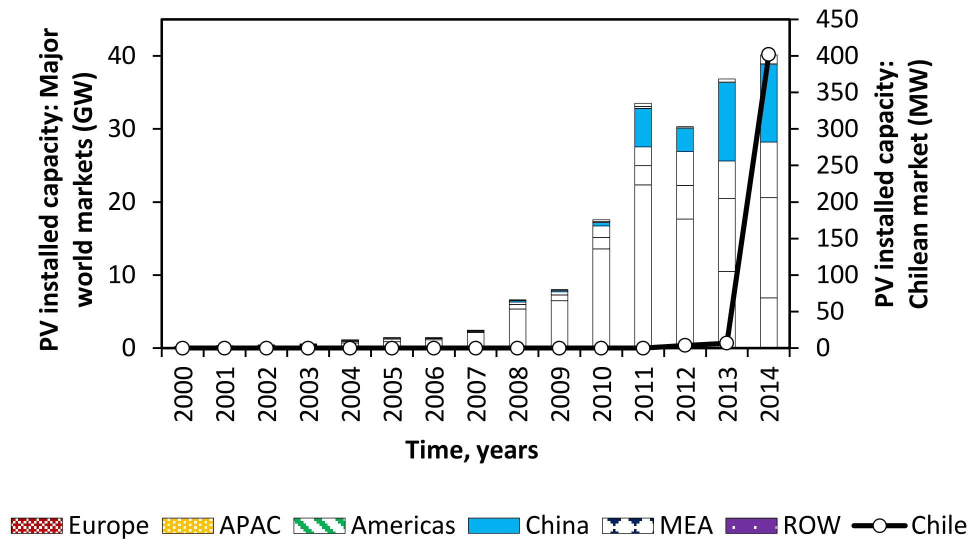

Figure 1-1: Photovoltaic annual installed capacity for major regions of the world (Swanson, 2006).

1.2.4 Small scale *PV:* at its tipping point to reach grid-parity in some markets without financial support due to significant cost reductions of technologies.

Cost of clean technologies are falling dramatically, both at the utility scale and for Distributed Energy Resources (*DER*s) at the end-user scale. For example, for the 2008 -2014 period, wind, distributed *PV*, utility-scale *PV* and Batteries have shown costs reductions between 73% and 41% as shown in Figure 1-2 (Schmalensee, 2015). As a consequence, these technologies have penetrated wholesale markets with the aid of financial or government incentives, thus becoming mainstream energy suppliers

(*Global Wind Report, Annual Market Update*, 2016; Tim Shear, 2016; Wirth & Schneider, 2017). Recently cost reductions of *PV* panels have gone one step further, this time penetrating markets without incentives, by reaching grid-parity in a few countries with outstanding solar resources. If cost continues to fall, many other countries would probably reach grid-parity in the future, making solar resources and incentives more and more irrelevant. Examples of these new revolutionized markets are *MENA* countries and Chile. In these places, *PV*-bid-offers in 2016 were registered at values as low as 24 *US$/MWh* for Abu Dhabi (Pothecary, 2016) and 29 *US$/MWh* for Chile (*Final Report of holesale electricity bid, refered to by article 131 of Chilean Electricity law*, 2016). At the end-user scale, *PV* has shown similar cost-reduction trends for small-scale applications[2] (Wirth & Schneider, 2017). Thus, it is reasonable to think that small-scale *PV* systems could also reach grid-parity in some countries, especially in places with high solar resources (Chung, Davidson, Fu, Ardani, & Margolis, 2015; Schmalensee, 2015).

[2] En este modelo no fue necesario establecer una definición de baja escala pues el ejemplo presenta una vivienda con un consumo reducido que no supera 2.5*kW*. Además, en la literatura no existe una definición de baja escala, pues no corresponde tampoco a baja tensión. En varios países hay límites para la tramitación simplificada de la generación distribuida que cambian de un sistema a otro (40*kW*, 100*kW*, 1*MW*, etc.).

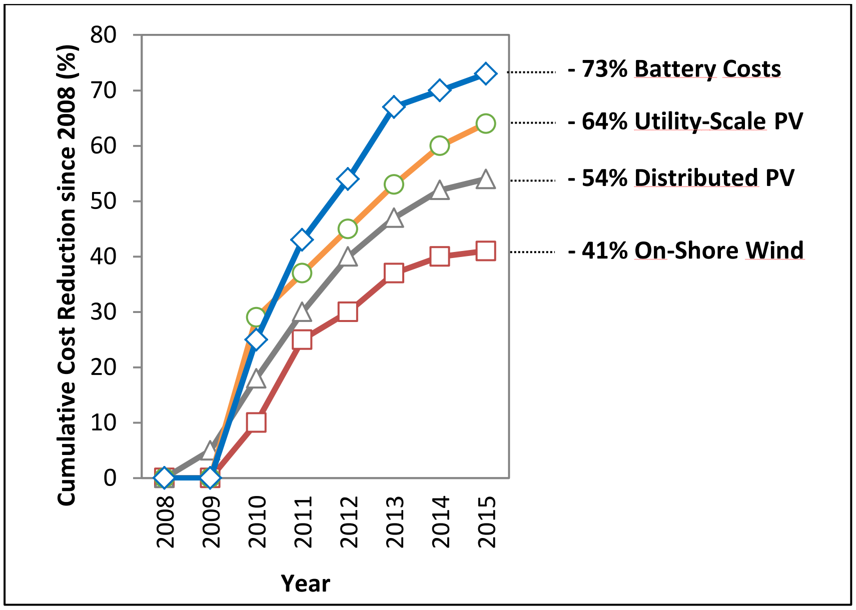

Figure 1-2: Impressive cost reduction of renewable energies and batteries for the years 2008-2015 according to The future of Solar Energy (*MIT*) (Schmalensee, 2015).

1.2.5 Financial institutions' and investors' risk perception. A main barrier for *PV* deployment.

Despite impressive growth, photovoltaic systems face various barriers to their development in several countries. These barriers commonly relate to the variability and risk of their generation. A large literature body tries to manage this variability by complementing *PV* with other resources such as batteries, hydroelectricity and wind generation (Cabral et al., 2010; Mahesh & Sandhu, 2015; Moghimi Ghadikolaei, Ahmadi, Aghaei, & Najafi, 2012). Equally important, but less present in literature, is the difficulty to obtain financing, since financial institutions perceive solar projects as riskier than conventional ones (Coenraads & Morotz, 2006).

1.3 Potential electricity end-users in developing countries: Access to electricity is critical for billions of people worldwide

In developing countries one of the main energy-related issues is access to electricity. In general, access to electricity is critical for the development of countries and societies around the world. Despite this fact,1.1 billion people (around 17% of world's population) have no access to this energy source (*Global Tracking Framework*, 2015, *World Energy Outlook 2015. Chapter 2: Energy Access*, 2015).

1.3.1 Access to electricity: Benefits and global efforts made

A large body of literature shows that access to electricity reduces poverty, enhances access to health-care and education, and boosts the economy, thus reducing poverty and improving quality of life (Deichmann, Meisner, Murray, & Wheeler, 2011). For example, an isolated community with a new electrical grid can deploy drinking water systems, irrigation systems, internet services, and can enable the arrival of new shops and industries. Although access to electricity is not sufficient enough to reach economic and social development, it is a barrier that must be overcome (Buchholz & Da Silva, 2010).

Therefore, important efforts have been made to boost electricity access by extending the central distribution grid (Schnitzer et al., 2014), essentially raising the worldwide electrification rate from 83% in 2010 to 85% in 2012 (222 million people gained access). However, many communities are still waiting for their electricity access due to several reasons. Among those, the high cost of extending the grid to remote and scattered populations seems to be making rural and remote communities lag behind (Bhandari, 2011; *Global Tracking Framework*, 2015).

1.3.2 Access to electricity in Latin America and the Caribbean impacts 25 million people in rural areas with scattered population.

In Latin America and the Caribbean (*LAC*), around 25 million people[3] have no access to electricity. For a region that aims to emerge from underdevelopment this is a very poor electricity coverage when compared to the developed world, e.g., *OECD* counties have electricity coverage of 100% (*Global Tracking Framework*, 2015).

To improve electrification coverage in *LAC* countries, governments have made important efforts during the 1990s and 2000s. Due to these efforts, *LAC*'s electrification coverage has significantly improved over the last years, increasing from 88% in 1990 to 96% in 2012, and has remained high - well above the world's average. As in the rest of the world, this improvement is mainly due to the expansion of the distribution system within areas under concession to a utility where they are obliged to provide service. These concession areas are very usual in *LAC* (e.g., Argentina, Bolivia, Chile and Peru) (Rudnick, Arnau, Mocarquer, & Voscoboinik, 2007) and tend to be defined around densely populated areas.

In rural areas, difficulties have emerged due to low population density (Yadoo & Cruickshank, 2010) or geographic remoteness (e.g., the Amazon and Andes regions).

[3] This number was calculated considering 623 millions inhabitants (*Concise Report on the World Polulation Situation in 2014*, 2014) and a 96% electrification (*Global Tracking Framework*, 2015)

Within these areas, governments - not as successful as they had hoped - have supported isolated communities by subsidizing stand-alone systems with specific technologies such as diesel, *PV* or wind. For a more in-depth review of the different rural electricity programs implemented in Latin America in the last 25 years see Annex B of Montecinos (Montecinos & Watts, 2015).

1.4 Objective of this Thesis: how to solve some very important difficulties that could arise from the new scenario in electricity systems at the end-user level for developed and developing countries

A revolution is happening today at the end-user level in developed countries and is just starting in developing countries due to the development and maturation of microgrids and its more service-oriented definition of Distributed Energy Resources (*DERs*). Almost the whole planet could benefit from this impressive paradigm shift: by offering new services and lower supply costs to end-users at the distribution level on one side, and improving quality of life in isolated communities by giving access to electricity on the other. Experience - together with academic literature - show that *PV* is a central technology in this matter.

The aim of this thesis is to contribute solving some very important difficulties that could arise with this new scenario. This translates into 3 main objectives, which are the following:

a) Correct *PV* system’s risk perception:

Quantify the bias produced by the ocean-atmospheric oscillations on the valuation of a *PV* project, which is one of the main barriers for its deployment due to financial institutions’ and investors’ risk perception.

b) Improve isolated community’s chance of success:

Provide a methodology that allows an isolated community to improve the sustainability of its electrical power supply through an approach based on optimal trade-off portfolio of microgrid designs that better adjusts to its needs. This could improve community’s satisfaction.

c) Understanding grid-tied end-user’s *DER* installation decision:

Provide a framework that allows understanding grid-tied end-user’s decision to install *DERs* under a netbilling regulation when faced with massive *DER* deployment, different tariff designs and *DER's* learning curves.

1.5 Thesis structure

The remainder of this thesis is organized as follows: Section 2 describes how the perceived risk of a *PV* project can be reduced using solar radiation prediction and ocean-atmospheric oscillations. Section 3 offers a novel methodology for microgrids in isolated communities using an electricity cost-coverage trade-off with 3-stage technology mix, dispatch & configuration optimizations. Section 4 proposes a framework to understand the decision of end-users to install *DER* under a netbilling regulation and calculates the impact of Distributed Energy Resources & tariff design on electrical distribution systems using microgrids and learning curves as a framework. Finally, section 7 offers a conclusion to this study.

2 FINANCIAL RISK REDUCTION IN PHOTOVOLTAIC PROJECTS THROUGH OCEAN-ATMOSPHERIC OSCILLATIONS MODELLING

2.1 Introduction

In recent years, photovoltaics (*PV*) have strongly penetrated the international energy markets at exponential growth rates, mainly driven by subsidies (Chilean Energy Ministry, 2008; "Chilean Renewable Energy Law (Modification)," 2013; European Commission, 2009, 2015; Heeter & Bird, 2013; McGinn et al., 2013; Pica Téllez et al., 2015) and by strong and sustained reductions of *PV* cell costs (Mints, 2014; Swanson, 2006). Europe led the installation of capacity until 2011. Since then, incentives were reduced in Europe and the market shifted to China, Japan and the USA (see Figure 1-1). In 2014 China was the main installer with 10.6 *GW* of the 40 *GW* installed that year. Next in relevance were Japan with 9.7 *GW*, Europe with 7 *GW* and the USA with 6.5 *GW*. However, all these markets sustained their growth (and explained their falls) due to subsidies and supporting policies (Rekinger et al., 2015).

2.1.1 Financial institutions' and investors' risk perception

Despite impressive growth, photovoltaic systems face various barriers to their development in several countries. These barriers commonly relate to the variability and risk of their generation. A large literature body tries to manage this variability through technical complementation with other resources such as batteries, hydroelectricity and wind generation (Cabral et al., 2010; Mahesh & Sandhu, 2015; Moghimi Ghadikolaei et al., 2012). Equally important, but less present in literature, is the difficulty to obtain financing, since financial institutions perceive solar projects as riskier than conventional ones (Coenraads & Morotz, 2006), a situation that this work aims to challenge.

Modern Portfolio Theory (*MPT*) developed by Novel Markowitz (Markowitz, 1952) assumes that the investor is risk averse and therefore prefers - from a set of different asset portfolios with equal expected profits - the one with the least profit variability. Beyond the purely financial world, this theory has been applied to real assets, particularly to energy projects. For example, *MPT* has been used multiple times to prove the ability of renewable energies to diversify energy sources and to improve energy security (Awerbuch, 1995, 2000; Awerbuch & Yang, 2007; Berger, 2003; DeLaquil, Awerbuch, & Stroup, 2005; Escribano Francés, Marín-Quemada, & San Martín González, 2013; Lesser, Lowengrub, Yang, Commission, & Bates White, 2007; Rodehorst, 2007).

2.1.2 Review of solar radiation and ocean-atmospheric oscillations in *PV* project's risk

Our bibliographic review takes a different and complementary path from *MPT*. We revised the literature related to the impact of predictable solar radiation and ocean-atmospheric oscillations (such as El Niño Southern Oscillation, *ENSO*) on the reductions of the investment risk of a single *PV* project before its inclusion into a portfolio. Existing voids in the literature are identified and original propositions are made when necessary.

The Chilean market was selected as a case study due to its outstanding solar potential, its booming solar *PV* market and its exposition to the most energetic ocean-atmospheric oscillation (*ENSO*), which affects the *USA* as well as several counties in Asia, Africa, Australia and the rest of America (Halpert & Ropelewski, 1992; Chester F Ropelewski & Halpert, 1996).

2.1.3 Relevance of the Chilean *PV* market

Chile now attracts international attention not only because it has the highest solar potential in the world (Mata-Torres, Escobar, Cardemil, Yeliz, & Matute, 2017), but also because it has become a precursor to unsubsidized markets, marking a turnaround. Chile is already the largest and fastest growing *PV* market in Latin America. The accumulated installation of photovoltaic systems in Chile has soared, growing from 10 *MW* in 2013 to 1.1 *GW* in 2016, reaching almost 2 *GW* in 2017 ("Total installed capacity of generation in Chile," 2017). Today, future growth is still being cross-subsidized due to system-wide costs that are a consequence of massive photovoltaic variable generation4. Also this cost is supported by more than 9 *GW* of projects approved by the environmental assessment system, which are competing to be finally developed ("Centre for Innovation and Promotion of Sustainable Energy,"

[4] In Chile - as well as in many other countries - system-wide costs produced due to photovoltaic variable generation are not internalized by those generation projects. Conversely, those costs are socialized with all stakeholders. Care should be taken with these costs, which are not considered in this study because they are relatively small at current *PV* penetration levels (Hirth, 2013), but could become significantly higher in the future.

n.d.). This trend - which is driven without any public policy aid5 by Chilean unique solar radiation and high electricity tariffs - may be followed by other markets if the cost reduction continues. According to the "Solar Power Europe" association, 5 *GW* are expected to be installed in Chile by 2019, which will position it as the main pole of solar development in Latin America (Rekinger et al., 2015).

2.1.4 Structure of the study

This study is organized as follows: Section 2 reviews the available literature related to the impact of predictable solar radiation and ocean-atmospheric oscillations on the reduction of the investment risk of a single *PV* project. Section 3 highlights voids present in the literature regarding climate predictability and *PV* investments. In section 4 a monthly profit model for investments in *PV* projects is proposed, specifically designed for financial risk assessments. In section 5 the importance of the Value Of Information (*VOI*) on partly predictable climate data for *PV* projects is highlighted and the use of variance decomposition to withdraw predictable components of profit from risk is explained. Section 6 shows and discusses Chilean Solar radiation resource, which is used for the case study developed. Section 7 reviews the three main ocean-atmospheric oscillations affecting Chilean climate along with their associated indexes and dynamics. Section 8 develops a predictive profit model that incorporates solar radiation and ocean-atmospheric oscillations. Section 9 presents the risk reduction achieved due to climate predictability for the

[5] Chile has a market share incentive for renewable energies, but this incentive is inactive because it has been overpassed largely since 2011 ("Centre for Innovation and Promotion of Sustainable Energy," n.d.).

selected case study (Chilean market) in 10 geographical zones. Section 10 extends the profit-risk model proposed for *PV* projects by including subsidies and discusses the potential impact of larger penetrations of renewable generation on the Chilean market driven by the risk reduction. Finally, section 11 offers a conclusion to this study.

2.2 Review of the impact of predictable solar radiation and ocean-atmospheric oscillations on the reduction of the investment's risk of a single *PV* generation project

Climate change has deepened the interest to deploy and encourage renewable energy generation around the world. Ironically, climate itself is one of the key barriers to obtain financing for renewable projects because financial institutions perceive solar projects as riskier than conventional ones. Climate change concern has also renewed the interest in understanding climate variability to predict and mitigate its future impact on society. Thus, growing interest has emerged regarding ocean-atmospheric oscillations (which are ocean-atmospheric climate anomalies) such as El Niño Southern Oscillation (*ENSO*), which impacts some regions of the planet with irregular periodicities of years or decades.

Despite the interest on climate and its evident impact on *PV* project risk, an extensive review of literature conducted as part of this research found no studies relating *PV* risk and climate and very limited literature on some other related subjects. In order to understand and detect the voids present in the literature, an extended review was conducted on key aspects that would finally enable the calculation of the financial risk reduction on a utility-scale *PV* project due to information contained in climate (solar radiation and ocean-atmospheric oscillations). This extended review allowed us to propose some original contributions that are included in this study. The main topics of this extended review are detailed in the following subsections.

2.2.1 Review of *PV* yield models for the long and short term

PV generation systems have nonlinear components (e.g., solar panels and inverters), nonlinear relations between components (e.g., inverter ratio) and nonlinear relations between radiation and ambient temperature (Corporation, 2011; Duffie, n.d.; Durisch et al., 2007; Myers, 2009). The strong presence of nonlinearities explains that in the short-term most publications of *PV* electricity production models use very detailed nonlinear relations between generation and radiation. Some common topics related to short-term production are energy management, regulation of netbilling/netmetering, statistical calculation of operational parameters and the short-term climate prediction (of a few days) (energy management (Sehar, Pipattanasomporn, & Rahman, 2016); regulation of netbilling/netmetering (Watts, Valdés, Jara, & Watson, 2015), statistical calculation of *PV* plant’s operational parameters (Andrews, Pollard, & Pearce, 2012; Khatib, Sopian, & Kazem, 2013; Limmanee et al., 2016) and the short-term climate prediction (Zamo, Mestre, Arbogast, & Pannekoucke, 2014a, 2014b)).

On the contrary, most studies of *PV* power generation that model the long-term use simple linear relationships between radiation and production. Within these linear models, most common topics are planning, market regulation, sizing and performance evaluation. (Planning (Gökmen et al., 2016; Wild, Folini, Henschel, Fischer, & Müller, 2015); market regulation (Spertino, Di Leo, & Cocina, 2013); sizing (Lambert, Gilman, & Lilienthal, 2006; Marion et al., 2005; Myers, 2009; Sukchai & Sirisamphanwong, 2014), *PV* plant and *PV* panel performance evaluation (Huld, Gottschalg, Beyer, & Topič, 2010; Ma, Yang, & Lu, 2013; Mondol, Yohanis, Smyth, & Norton, 2006; Sharma & Chandel, 2013). The studies of Wild (Wild et al., 2015) and Huld (Huld et al., 2010) are exceptions focusing within the long-term modeling, since these include logarithmic relations between radiation and temperature in *PV* panel efficiency models.

2.2.2 Review of *PV* profit models and the long-term financial risk

Many articles list, mention and quantify risk in renewable projects and specifically in utility-scale solar projects. A revision of the literature of financial risks in utility-scale *PV* projects was conducted, showing that risk is modeled in many ways, such as: a) financial methods that support investment and funding decisions (mean variance portfolios, *CAPM*, *VACC*) (Albrecht, 2007; Szabó, Jäger-Waldau, & Szabó, 2010; Tajeddini, Rahimi-Kian, & Soroudi, 2014), b) AutoRegressive Mean Average models (*ARMA*) for wind speed (Parastegari, Hooshmand, Khodabakhshian, & Zare, 2015), c) stochastic processes to model prices (Geometric Brownian Motion, Markov Regimen Switch) (Biondi & Moretto, 2015; Nikolaidis, Milidonis, & Charalambous, 2015), risk indicators (Value at Risk - *VaR*, Conditional Value at Risk - *CVaR*, among others) (Cebecauer & Suri, 2015; Tajeddini et al., 2014), learning curves (Albrecht, 2007; Biondi & Moretto, 2015), probability distribution functions (wind using Weibull, solar radiation using Gamma and electricity prices using Gauss)

(Tajeddini et al., 2014), real options (Biondi & Moretto, 2015) and Montecarlo method for the measurement of risk based on *NPV* (F. Bustos, Toledo, Contreras, & Fuentes, 2016).

The need to develop a new methodology to specifically analyze risk in a long-term, utility-scale *PV* projects was highlighted by a second bibliographic review that was conducted as part of this study. This review found no studies relating long-term risks of utility-scale *PV* projects to income and cost (profit) models.

2.2.3 Review of the relation of the Value Of Information and solar energy

With regard to solar energy, literature linked with Value Of Information (*VOI*) is very scarce. As far as we could find, only the work by Sen (Sen, 2004) relates solar energy generation with satellite information within a broader valued enumeration of the impact of satellite information. He bases this relation on a report of SANDIA (Ivey, Akhil, Robinson, Stamber, & Stamp, 1999) and another of *NASA* (Whitlock & Stackhouse, 2002). However, literature that associates *VOI* with the risk to invest and/or with inter-annual oceanic-atmospheric modeling has not been found for the energy industry.

Value Of Information associated with climate can be thought of as the predictable part of climate. Although there is a large literature body on modeling solar radiation, there are no studies that assess quantitatively the risk reduction faced by the investor when new information contained in a solar radiation models is factored in.

2.2.4 Review of the use of variance decomposition in *PV* systems

Variance decomposition of a *PV* project's profit can help to analyze the risk reduction that an investor may achieve by using the information contained in solar radiation and climate. A review, conducted as part of this study, discovered only the study of Kumpf (Kumpf, Blumsack, Young, & Brownson, 2015) applied this technique to a *PV* system. This work decomposes variance of income (considering that income is the product of the selling price of energy and the power injected into the grid). However, there are no studies that either decompose the variance of profit (income - costs) or explicitly incorporate solar radiation in *PV* projects, which inspired this proposed model.

2.2.5 Review of the ocean-atmospheric oscillations discovered

Ocean-atmospheric oscillations are key vehicles in the planet's climate system and they affect climate anomalies of each geographic area in different ways. A review of the ocean-atmospheric oscillations (National Center for Atmospheric Research, 2015) that have the potential to impact wind, hydraulic, solar and biomass energy production was conducted as part of this study. These oscillations are El Niño Southen Oscillation (*ENSO*) (Cane, 2005; Halpert & Ropelewski, 1992; C F_ Ropelewski & Halpert, 1989), Madden-Julian Oscillation (*MJO*) (Madden & Julian, 1971), North Atlantic Oscillation (*NAO*) (Hurrell & Deser, 2009), Interdecal Pacific Oscillation (*IPO*) (Dong & Dai, 2015), Pacific Decadal Oscillation (*PDO*) (Mantua & Hare, 2002), Arctic Oscillation o Northern Annular Mode (*AO* or *NAM*) (Thompson & Wallace, 1998), Antarctic Oscillation o Southern Annular Mode (*AAO* o *SAM*) (G. J. Marshall, 2003; “Southern Annular Mode,” 2015) and Indian Ocean Dipole (*IOD*) (“Indian Ocean,” 2015; Saji, Goswami, Vinayachandran, & Yamagata, 1999), Atlantic Multi-Decadal Oscillation (*AMO*) (Drinkwater et al., 2014). The number of oscillations could be reduced by one because *NAO* and *NAM* are claimed to be indistinguishable (Feldstein & Franzke, 2006).

2.2.6 Review of studies relating ocean-atmospheric oscillations and electricity generation

Some ocean-atmospheric oscillations, such as *ENSO* and *NAO*, and their impact on the generation of electrical energy have been studied with focus on hydropower (George, Waylen, & Laporte, 1998; Quijano H, Botero B, & Domínguez B, 2012; Smith & Semazzi, 2014; Trigo et al., 2004; Voisin et al., 2006). Wind energy has also been studied more recently but in less depth (Harper, 2005; Klink, 2007; X. Li, Zhong, Bian, & Heilman, 2010; Renwick, Mladenov, Purdie, McKerchar, & Jamieson, 2010). However, little has been published regarding their impact on solar radiation and even less concerning their impact on solar power (photovoltaic and thermosolar).

Exceptions linking ocean-atmospheric oscillations with solar radiation are i) Davy's work (Davy & Troccoli, 2012) that maps the percentage differences of Global Horizontal Radiation (*GHI*) between the opposite phases for *ENSO* and *IOD* in Australia (Figure 2-1), ii) Pozo-Vazquez (Pozo-Vázquez, Tovar-Pescador, Gámiz-Fortis, Esteban-Parra, & Castro-Díez, 2004) who presents a map linking the North Atlantic Oscillation (*NAO*) with the sunshine duration and radiation in Europe and

iii) Passad (Prasad, Taylor, & Kay, 2015) who correlates geographically Direct Normal Irradiance (*DNI*) with the cloud amount and also correlates the cloud amount with *ENSO* in Australia using *SOI*. The non-existence of studies associated with solar energy for the south-east Pacific coast (South America) motivates this study.

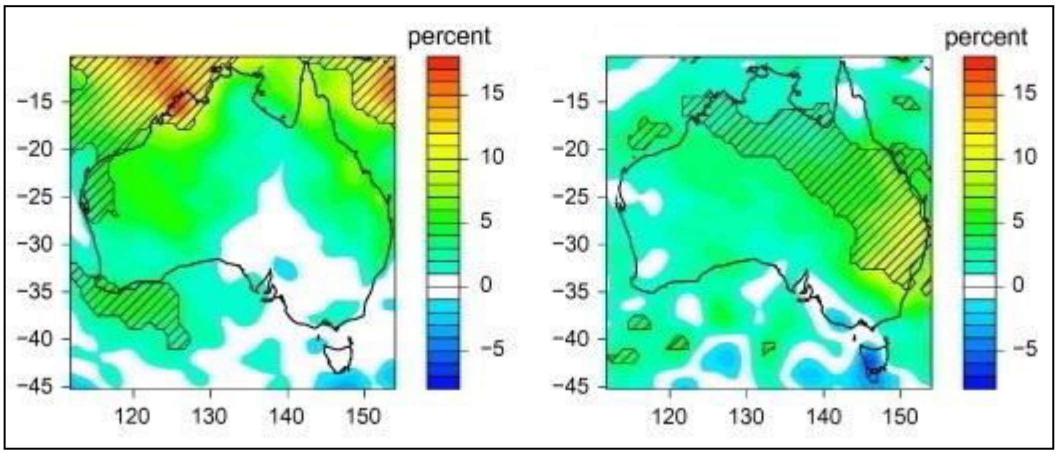

Figure 2-1: Variation of solar radiation in Australia due to *ENSO*. Phase difference between El Niño and La Niña is more than 10% in some locations. (a) Southern Hemisphere summer (December-February). (b) Southern Hemisphere winter (June to August). Hatch pattern areas are statistically significant (Davy & Troccoli, 2012).

2.3 Voids in literature: Impact of solar radiation and ocean-atmospheric oscillations on the risk of *PV* projects and in portfolios of electricity generation in Chile

For investors who want to minimize their risk exposure in energy projects it is essential to understand their energy resources. Particularly for photovoltaics it is important to understand the solar resource dependency on climatic variations and its compensation in time. Therefore, investors must focus on variations of long-term climatic anomalies. Literature in this context is poor and contains very few studies that only contribute to some aspects of the problem (e.g., to establish the relationship between solar radiation and some ocean-atmospheric oscillations).

Motivated by the literature reviews of this study, the voids found in literature to calculate the financial risk reduction of information contained in predictable solar radiation and ocean-atmospheric oscillations are listed next:

- Relation between *PV* risk reduction and climate predictability for investment decisions.
- Development of an income and cost (profit) model for long-term risks of utility-scale *PV* projects.
- Relation between Value of Information (*VOI*) and investment risk.
- Relation between *VOI* and oceanic-atmospheric oscillations in the energy industry.

  Decomposition of variance of profit (income – costs) or decomposition of variance incorporating explicitly solar radiation in the *PV* projects, although variance decomposition is used in well-developed knowledge areas.

- Relation between solar energy and ocean-atmospheric oscillations in the south-east Pacific coast (South America).
- Incorporation of climate information asymmetries for different investors with dissimilar predictive models (different information of solar radiation) related to an individual photovoltaic projects. This void in literature can only be addressed if other more basic voids are studied.

2.4 A Profit model for the investment's risk assessment in *PV* projects

2.4.1 Incomes and costs of a *PV* plant

The annualized profit of a photovoltaic plant is the difference between the income generated by selling their products I_t and their costs C_t (2.1). The main income relates to the sale of electric energy in different markets $I_{E,t}$, which is the product of the electricity produced by the plant E_t and the sales price of that energy $P_{E,t}$ (2.2).

In many electricity markets other products can be sold (2.3) such as firm power capacity $I_{P,t}$ or green certificates (mandatory quotas associated with renewable) $I_{GC,t}$, and more recently ancillary services (reserves, load following, etc.) $I_{AS,t}$ (Contreras, Frantzis, Blazewicz, Pinault, & Sawyer, 2008). In developing countries that signed and ratified the Kyoto Protocol, PV projects can also sell Certified Emission Reduction units (*CER*), obtaining an income $I_{CDM,t}$ that depends on the energy produced E_t, the selling price of the certificate $P_{CDM,t}$ and the emission factor of the power grid EF to which energy is injected (2.4) (Watts, Albornoz, & Watson, 2015)[6]. These relationships are shown below.

$$\pi_t = I_t - C_t \tag{2.1}$$

$$I_{E,t} = E_t P_{E,t} \tag{2.2}$$

$$I_t = I_{E,t} + I_{P,t} + I_{GC,t} + I_{AS,t} + I_{CDM,t} \tag{2.3}$$

$$I_{CDM,t} = E_t P_{CDM,t} EF \tag{2.4}$$

Annualized income and costs are converted to present value, being discounted at a certain discount rate r that pays off capital and business risks. For a review of the structure of discount rates and risk premiums of renewable projects in various countries of *LATAM* see (Watts, Albornoz, et al., 2015).

The costs of a photovoltaic project are mainly associated with its development and therefore are essentially investment costs C_{INV} (panels, inverters, balance of plant, etc.) and to a much lesser degree operation and maintenance $C_{O\&M,t}$ (*O&M*) (Contreras et al., 2008), which do not depend on the production level, either. We neglect costs of ancillary services $C_{AS,t}$ from our cost analysis of PV projects because their impact due to their generation variability is usually small at system level. For example, costs of operating reserves are normally less than 2% (Pudjianto, Djapic, Dragovic, & Strbac, 2013) (Hummon et al., 2013). Also, regulations usually miss to charge these costs (e.g., Chilean regulation) to individual projects, simply adding these costs to customers.

Investment costs are determined through optimal sizing of module angle, module number and - in case of a stand-alone system – batteries (Cabral et al., 2010; Watts,

[6] Subsidies, which are not included here, are studied in detail in section *10. Model extension and discussion.*

Valdés, et al., 2015). These Investment costs have been falling steadily and in Chile are currently in the range of 1200-1700 *USD / KW* for plants above 0.5 *MW*. Such costs can be annualized (*AVI*) on the economic lifetime of the plant (e.g., $n = 20$) remunerating the capital with a rate r as shown in (2.5). Furthermore, since operation and maintenance costs $C_{O\&M,t}$ are essentially annual costs, the total annualized cost C_t is the sum of annualized investment costs *AVI* and the operation and maintenance costs (2.6), as shown below.

$$AVI = \frac{rC_{INV}}{1-(1+r)^{-n}} \tag{2.5}$$

$$C_t = AVI + C_{O\&M,t} + C_{AS,t} \tag{2.6}$$

Given the current international situation of Certified Emission Reduction (*CER*) units (almost zero prices of *CDM*[7] certificates) and the Chilean regulation (which does not allow to sell or buy ancillary services to *PV* plants and pays very little firm power), income for *PV* plants depends mainly on the energy sold. This energy is usually sold at a fixed price under a Power Purchase Agreement (*PPA*) to reduce the risks of exposure to changing spot prices and ensure steady income to obtain financing.

2.4.2 Energy conversion model for the long term

The average daily production of electricity depends on the average daily Global Horizontal Radiation (GHR_t), the gain associated with the angle of the solar panels R_{Gain}, the area of these panels A and the energy conversion efficiency (from radiation to electricity) η_{sys} (2.7). This efficiency can be divided in module efficiency η_m and

[7] Clean Development Mechanism

the efficiency of the balance of system (2.8). This last efficiency is called Performance Ratio (*PR*) and depends mainly of the following deratings (2.9): a) power losses of nearby shadows η_{sh}; b) incident angle modifier η_{IAM}; c) module degradation η_{deg}; d) temperature η_{tem}; e) mismatch effect η_{mis}; f) soiling η_{soil}; g) wiring η_{mpp}; h) maximum power point η_{mpp}; i) inverter η_{inv} (Marion et al., 2005; Watts, Valdés, et al., 2015). These efficiencies are shown below.

$$E_t = GHR_t \cdot R_{gain} \cdot A \cdot \eta_{sys} \tag{2.7}$$

$$\eta_{sys} = \eta_m \cdot PR \tag{2.8}$$

$$PR = \eta_{sh}\eta_{IAM}\eta_{deg}\eta_{tem}\eta_{soil}\eta_{mis}\eta_{net}\eta_{mpp}\eta_{inv} \tag{2.9}$$

Furthermore, the *PV* module efficiency η_m at 25ºC and 1.5 *AM* can be expressed as shown in the following equation (Durisch et al., 2007),

$$\eta_m = p \cdot \left[q \cdot \frac{GHI}{GHI_0} + \left(\frac{GHI}{GHI_0}\right)^m\right] \cdot (2 + r + s) \tag{2.10}$$

where *GHI* is the Global Horizontal Irradiance, GHI_0 is a constant equal to 1000W/m^2 and the parameters are module specific. For this work the module of Kyocera LA361K51 was used with parameters p = 15.39, m = 0.0794, q = -0.177, r = -0.09736 and s= -0.8998.

Efficiency associated with temperature's derating effect on the module η_{tem} is calculated using the Normal Cell Operating temperature (*NOCT*) methodology (Duffie, n.d.; Notton, Lazarov, & Stoyanov, 2010),

$$T_c = T_a + \frac{GHI}{GHI_{NOCT}}\left(T_{NOCT} - T_{a,NOCT}\right)\left(1 - \frac{\eta_{Tref}}{\tau\alpha}\right) \tag{2.11}$$

$$\eta_{tem} = 1 - \eta_m\beta_{ref}\left(T_c - T_{ref}\right) \tag{2.12}$$

where T_{NOCT} = 45ºC obtained from a wind velocity v = 1m/s, $T_{a,NOCT}$ = 20ºC and GHI_{NOCT} = 800W/m^2. Additionally, the efficiency of the module for the *NOCT* conditions are $\eta_{Tref} = 0.127$.

The efficiency of the inverter η_{inv} can be expressed according to the equations published by Notton (2.13) – (2.16) (Notton et al., 2010),

$$\eta_{inv} = \frac{p}{p+p_0+kp^2} \tag{2.13}$$

$$p_0 = \frac{1}{99}\left(\frac{10}{\eta_{10}} - \frac{1}{\eta_{100}}\right) - 9 \tag{2.14}$$

$$k = \left(\frac{1}{\eta_{100}}\right) - p_0 - 1 \tag{2.15}$$

$$p = \frac{P_{out}}{P_{inv,nom}} \tag{2.16}$$

where P_{out} is the *AC* inverter's output power, $P_{inv,nom}$ is the nominal capacity of the inverter, η_{10} is the efficiency of the inverter at 10% nominal capacity and η_{100} is the inverter's efficiency at 100% of the inverter's nominal capacity. In this work an inverter with η_{10}=*93% and* η_{100} = *96%* was used.

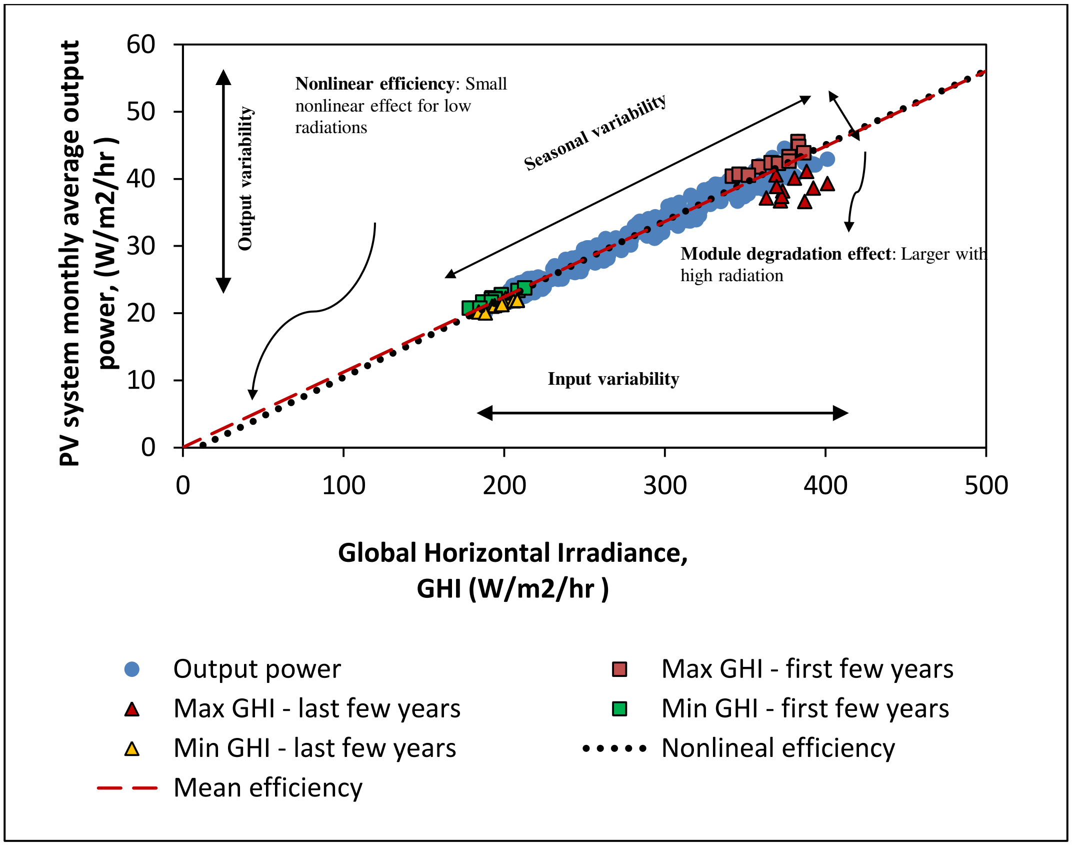

Figure 2-2: Output power Pt and monthly average of Global Horizontal Irradiance $\overline{GHI}_m$ of a photovoltaic plant with modules' degradation of 0.5%.

Despite the nonlinear component of the photovoltaic plant model (2.7) - (2.16) in the time range from minute to hours, this nonlinearity tends to disappear in conditions of increased radiation and energy production. This explains why PV systems tend to move in the linear region of the model for longer term applications which also integrate monthly radiation. The relationship between the monthly average Global Horizontal Irradiance (*GHI*) and the monthly average electricity output power is almost linear, as for example in the city of Calama, in the north of Chile (adjusts with

R^2 = 0.9750) shown in Figure 2-2. This relationship uses a zero intercept and has an average efficiency of $\bar{\eta}_{sys}$ =10.52% for the system. This simplification is based on the fact that a nonzero intercept does not substantially improve the fit (R^2 = 0.9751). The dispersion that occurs with respect to the linear regression is mainly due to the efficiency degradation of the modules, which has units of percentage and thus is greater for larger radiations than for smaller radiations. Also it is important to emphasize that the variability which best explains the average monthly electric power output of the photovoltaic plant is the seasonal variability.

Although the nonlinearity of the total energy conversion efficiency is almost negligible, it has a small effect that tends to correct the electric power generated at small radiation levels downward with respect to the linear relationship.

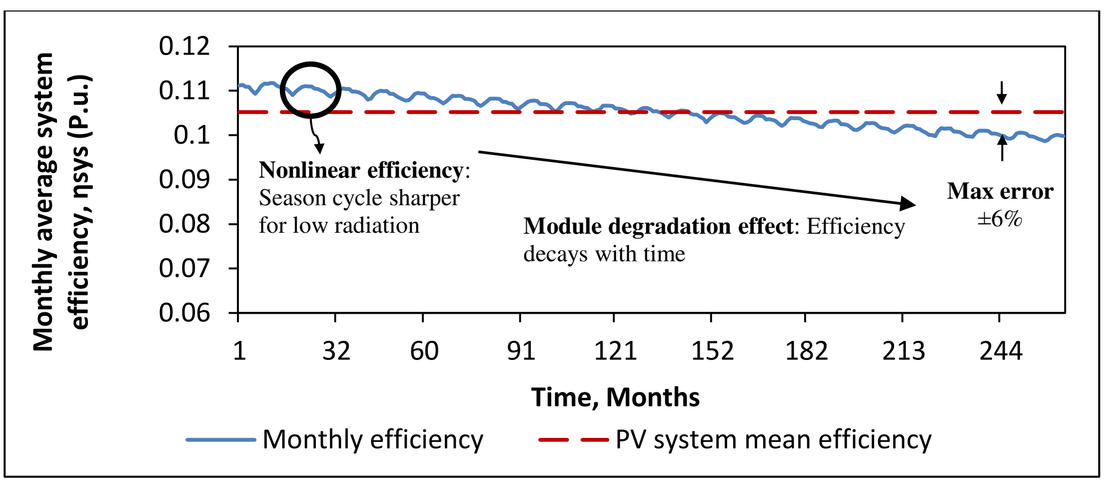

Figure 2-3: Efficiency of the photovoltaic system ηsys: Evolution in time for a photovoltaic plant with modules' degradation of 0.5%.

The average monthly system efficiency η_{sys} decays over time due to the effect of the degradation of the modules as shown in Figure 2-3. This ultimate degradation remains bounded within ± 6% of the average efficiency for the entire evaluation horizon used (244 months).

Besides, due to the nonlinearity of the system, the average monthly efficiency is deformed over time compared to the monthly Global Horizontal Radiation (*GHI*) that has a sinusoidal behavior (Figure 2-3). In a perfect linear relationship, because *GHI* is sinusoidal, the electric power generated will be sinusoidal as well. However, a deformation of the electric power that flattens/shortens the maximums and stretches/lengthens the minimums of the sinusoid is observed. Though, this effect is very minor because of its almost-linear behavior in the range evaluated.

Table 2-1: Basic information of *PV* plant (10 areas of Chile). Global Horizontal Radiation, energy conversion's mean efficiency, Determination Coefficient, geographical coordinates and optimal module angle.

Chilean City	Glob. Horiz. Rad. GHI (kWh/m^2/Day)	Syst. Eff. $\overline{\eta}_{sys}$ (%)	Det. Coeff[b] R^2 (%)	Det. Coeff[c] R^2 (%)	Lat.	Lon.	Opt. Angle Gain[a] R_{gain}
Iquique	5.28	10.32	98.98	98.83	-20.21	-70.14	1.034
Calama	6.90	10.52	97.51	97.50	-22.45	-68.92	1.064
Antofagasta	5.36	10.34	98.88	98.75	-23.65	-70.40	1.052
Copiapó	4.93	10.32	98.71	98.47	-27.36	-70.33	1.090
Coquimbo	5.01	10.32	98.76	98.47	-29.96	-71.33	1.082
Ovalle	5.06	10.32	98.89	98.64	-30.59	-71.19	1.089
Valparaíso	5.25	10.30	99.20	99.03	-33.04	-71.62	1.047
Santiago	5.47	10.33	99.24	99.14	-33.43	-70.65	1.084
Concepción	5.19	10.26	99.33	99.17	-36.81	-73.05	1.090
P. Montt	3.84	10.01	99.48	99.15	-41.47	-72.93	1.0615

[a]A optimal PV module angle gain R_{gain} was obtained from (Watts, Valdés, et al., 2015) for 10 Chilean cities.

[b] Intercept≠0

[c] Intercept=0

For a photovoltaic power plant located in Chile between 20ºS (Arica) and 40ºS latitudes (Puerto Montt) monthly nonlinear effect for the energy conversion efficiency is generally negligible. This is presented for 10 geographical areas where the fit of a linear regression with intercept equal to zero is very good (Table 2-1). For these 10 areas the average monthly efficiency moves between 10.01% and 10.52% and the coefficients of determination R^2 with zero intercept between 97.50% and 99.15% (R^2 with nonzero intercept between 97.51% and 99.48%).

It is noted that using the average monthly efficiency as a replacement for the instantaneous efficiency of the system is a good approximation for a photovoltaic system whose incident radiation has a time resolution of at least 1 month and degradation of modules at most 0.5% annually in Chile. In reality, the adjustment will be even better, because nowadays it is easy to find manufacturers of modules on the market that guarantee similar degradations[8]. These guarantees of degradation are generally higher than actual measurable degradation in the field. So for example, for Calama, 0.3 and 0.4 degradations will correspond to a zero intercept adjustments R^2 = 0.9911 and R^2 = 0.9841 respectively (for non-zero intercept R^2 = 0.9913 and R^2 = 0.9843 respectively) (Sunpower, 2012).

Global Horizontal Radiation used in Figure 2-2 and Figure 2-3 was obtained from *NASA* for the period 1984 and 2005 with a spatial resolution of 1° lat./long. (Stackhouse, n.d.). The gain due to the optimum inclination of the photovoltaic panels published by Watts (2015) was used for the 10 areas presented and an area

[8] For example, SunPower modules usually guarantees a minimum energy performance of 95% for the first five years and then for an annual degradation of 0.4% until year 25, ending in minimum efficiency of 87% after the entire period.

equal to a square meter (A = 1m^2) as shown in Table 2-1. In addition, the Kyocera module LA361K51was used which, with a nominal power P_p = 51 W_p and an area of 98.5cm × 44.5 cm, results in a per square meter installed power of 0.116 kW (nominal power used by the investor). Finally, an annual 0.5% degradation was used, and the other efficiencies were obtained from Watts (η_{sh}=98%, η_{IAM}=98%, η_{soil}=95.5%, η_{mis}=97%, η_{net}=99% y η_{mpp}=99%) (Norton et al., 2011).

The average daily generation of electric power[9] for each month E_m can be expressed (2.17) using the transfer function of the photovoltaic plant (2.5) - (2.6), the gain associated with the angle R_{Gain} photovoltaic panels and the area of such panels A. These two last parameters do not depend on time t, and are constant for a particular project,

$$E_m = (\frac{1}{\mathrm{d}_m}) \cdot R_{gain} \cdot A \cdot \sum_{t=1}^{d_m}(GHR_t \cdot \eta_{sys}), \tag{2.17}$$

where d_m is the number of days of the correspondent month.

It is possible to use the average monthly efficiency of the photovoltaic plant $\bar{\eta}_{sys}$ to replace the instantaneous efficiency without much loss of information due to its almost constant electrical output, considering a time resolution of 1 month and a degradation of PV modules of 0.5% (for Calama error reaches a maximum of ± 6% for 244 months horizon shown in Figure 2-3), which allows the conversion of (2.17) into (2.18).

$$E_m = (\frac{1}{d_m}) \cdot R_{gain} \cdot A \cdot \bar{\eta}_{sys} \cdot \sum_{t=1}^{d_m} GHR_t \tag{2.18}$$

---

[9] Average daily energy generated E_m for each month is calculated using the 24 hours.

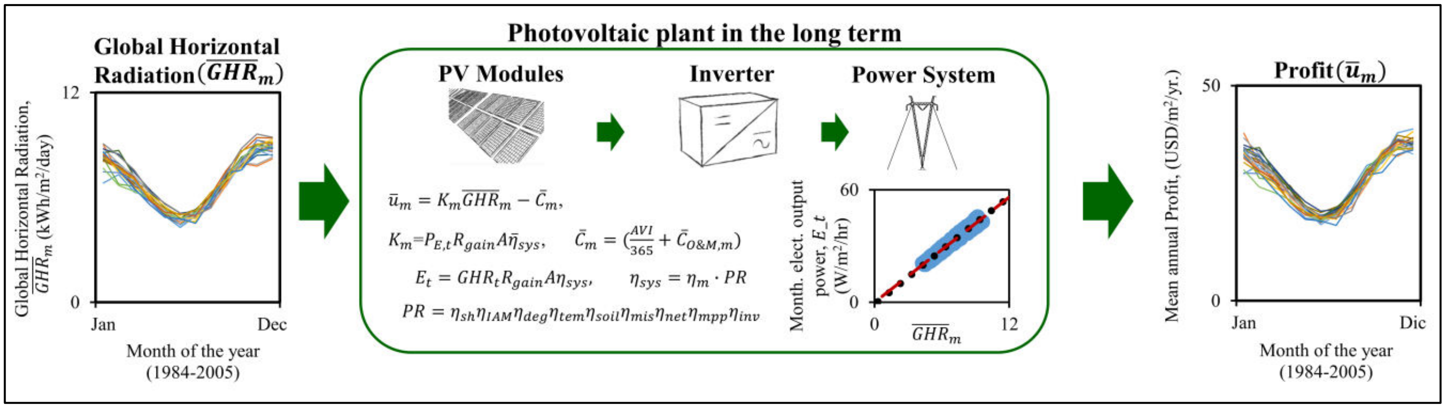

Figure 2-4: Impact of radiation variability on profit variability. Monthly relationship is nearly linear.

In turn, considering that the average daily Global Horizontal Radiation per month is $\overline{GHR}_m = (1/d_m)\cdot\sum GHR_t$, the daily average electric power per month injected into the power system can be written as a direct proportion of the daily average radiation per month, which is the model used to represent the power generation of a photovoltaic plant in this study (2.19). This model is represented schematically in Figure 2-4.

$$E_m = R_{gain} \cdot A \cdot \bar{\eta}_{sys} \cdot \overline{GHR}_m \tag{2.19}$$

2.4.3 Risk structure and profit model

Considering only the decomposition of income and costs of the profit, the major risks for investors in a photovoltaic project are related to their income, since the costs are well protected through the negotiation of contracts for procurement of equipment and balance of plant or through turnkey contracts that are commonly performed.

The risks associated with revenue often depend on the variations in the amount of electricity fed into the grid and on the price of this electricity. The amount of injected electricity can be modeled in the long term (≥ 1 month) through a linear regression, where the independent variable is the solar radiation, assuming that the produced power is always dispatched, given their low marginal costs (priority of dispatch). Prices depend in turn on the electricity market where the investor sells his/her energy. In general, to mitigate the risks associated with the price and improve the bankability of the project, developers must have a *PPA*, which commonly covers the entire production.

Costs have less impact on risk than income. Investment costs in photovoltaic projects are high but have a low variability, given that those costs are incurred at the beginning of development and are well known at the time of investment (being the investor protected through contracts). Moreover, in places with normal or low levels of dust and close water access, *O&M* costs are low and its variability is of limited impact (Contreras et al., 2008).

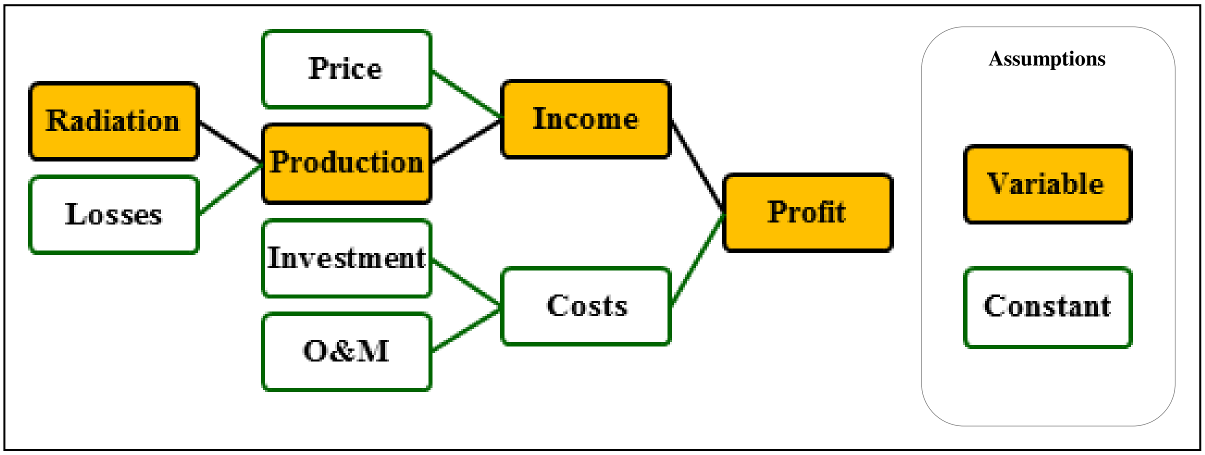

Figure 2-5: Breakdown of incomes, costs and related assumptions. Filled blocks (yellow) are regarded as variables due to the variability in solar radiation. Blank blocks with green edge are regarded as constant.

Given the nature of risk for costs and income of a *PV* plant, it is possible to make the following assumptions shown in Figure 2-5: a) losses (or equivalently the energy conversion efficiency) are constant (considering the long term; see explanation in subsection 2.2 above called *Energy conversion model for the long term*); b) price of energy is constant (through the use of Power Purchase Agreements (*PPA*) at a fixed price); c) costs are constant (because investment costs are known and protected by contracts and because the operation and maintenance costs are low and have a limited impact). Therefore, the monthly profit can be expressed as a linear function of the average daily radiation for each month $\overline{GHR}_m$ based on (2.19) as presented below,

Monthly Profit:

$$u_m = P_{E,t} R_{gain} A \bar{\eta}_{sys} d_m \overline{GHR}_m - C_m \tag{2.20}$$

$$C_m = \left(\frac{AVI}{365} + \bar{C}_{O\&M,m}\right) \cdot d_m \tag{2.21}$$

where $P_{E,t}$ is the electricity energy price injected to the power system (constant), R_{gain} is the gain related to the optimal inclination of the PV panels, A is the panels' area, $\bar{\eta}_{sys}$ is the energy conversion efficiency (constant), d_m is the number of days of the corresponding day and C_m is the monthly cost (constant) which is obtained from the annualized investment cost (AVI), and the daily $O\&M$ mean cost for each month $\bar{C}_{O\&M,m}$(2.19). For an example of the costs of operation and maintenance in Chile see (Fuentealba et al., 2015).

To become independent of the number of days in a month d_m, the daily average net income per month $\bar{u}_m$ can be used, corresponding to the following equation:

Daily mean Monthly Profit:

$$\bar{u}_m = {}^{u_m}/_{d_m} \qquad \bar{u}_m = P_{E,t}R_{gain}A\bar{\eta}_{sys}\overline{GHR}_m - \bar{C}_m \tag{2.22}$$

$$\bar{C}_m = {}^{C_m}/_{d_m} \qquad \bar{C}_m = (\frac{AVI}{365} + \bar{C}_{O\&M,m}) \tag{2.23}$$

where $\bar{C}_m$is the daily mean cost for each month (constant).

This is equivalent to saying that the daily average profit of a month $\bar{u}_m$ and the daily average radiation of the same month $\overline{GHR}_m$ have a linear relationship with a proportionality constant K_m as transfer function. This relation is presented in the following equations.

$$\bar{u}_m = K_m\overline{GHR}_m - \bar{C}_m, \text{where, } K_m{=}P_{E,t}R_{gain}A\bar{\eta}_{sys} \tag{2.24}$$

where K_m depends of $P_{E,t}$, the optimal PV panel inclination gain R_{Gain}, the panel area A, the mean energy conversion efficiency of the plant $\bar{\eta}_{sys}$ and the days in a month d_m.

The annual profit u_a is obtained by summing up the monthly profits u_m, which involves adding the daily averages for each month weighted by the number of days in each month as shown below.

Annual Profit:

$$u_a = P_{E,t} \cdot R_{gain} \cdot A \cdot \bar{\eta}_{sys} \cdot GHR_a - C_a,$$

$$\text{where } GHR_a = \sum_{m=1}^{12} d_m \cdot \overline{GHR}_m$$

$$\text{and } C_a = \sum_{m=1}^{12} d_m \cdot \bar{C}_m \qquad (2.25)$$

Analogous to the monthly radiation, it is possible to establish a relationship of direct proportionality between the annual Global Horizontal Radiation GHR_a and the annual profit with a proportionality constant $K_a = K_m$.

For example, for Calama $K_a = K_m = 0.10 \cdot 1.0643 \cdot 1 \cdot 0.10524 = 11.201 \cdot 10^3 \cdot USD \cdot m^2/kWh$ according to (2.24) and $AVI = 170 \cdot USD/kWh/year$ according to (2.5). Using (2.21) and (2.23) $\bar{C}_m = 6.05 \cdot 10^{-3} U \cdot SD/day$. This is obtained by taking into account the sale price of electricity $P_{E,t} = 0.10 \cdot USD/kWh$, a *PV* panel area $A = 1m^2$, the discount rate $r = 10\%$, the evaluation horizon $n = 20$, the investment cost $C_{INV} = 1450 \cdot USD/kWh$, *O&M* cost $\bar{C}_{O\&M,m} = 6.210 \cdot 10^{-3} U \cdot SD/day$ and the installed capacity of $0.116 \cdot kW/m^2$ (the latter due to *PV* module Kyocera LA361K51 used).

2.5 Risk reduction through the Value of Information

Having found a long-term linear model for the profit in terms of solar radiation (the main variable in the long run), the development of a methodology that uses this model and information to reduce the risk of the investor is of great interest. In other words, it is relevant to understand, from the investor's point of view, the value of the information contained within the solar radiation, since more of this information reduces the risks of investing in photovoltaic projects.

2.5.1 Value of Information and solar energy

The Value of Information (*VOI*) is the willingness-to-pay (by the investor) for information to improve the financial result of an investment under uncertain future scenarios. Economically, at the margin, the investor would buy information until the marginal cost of acquiring information equals the expected marginal benefit of using it. The new information may lead to create new alternatives to improve the expected outcome of the project or review and update the probabilities of certain future scenarios, given new relevant information (Mian, n.d.; Quirk, 1987; Schuyler, n.d.).

2.5.2 Risk reduction through solar radiation modeling

From the standpoint of *VOI*, before an investor includes a project based on photovoltaics into its optimum investment portfolio, the individual project risk should be reduced using all the information available. Predictive models of climate and solar radiation can provide information because these variables are partially predictable.

Although there is a large literature body modeling solar radiation, there are no studies that assess quantitatively the risk reduction that new information contained in a solar radiation model contributes to the investor.

2.5.3 Investment risk decomposition

When considering a portfolio of power generation projects, the Modern Portfolio Theory (*MPT*) does not consider information asymmetries (all investors have the same information) and calculates the risk of each project as the standard deviation of its profit or return. Given this assumption, *MPT* shows that it is possible for a portfolio to diversify risk as long as the various asset risks tend to cancel each other out. This means that the total risk of the portfolio is less than the sum of the risks of each of the assets that comprise it.

However, for individual photovoltaic projects, information asymmetry will exist as long as there are investors with different predictive models that incorporate information about solar radiation. This radiation largely defines the net profit of these projects (2.20) - (2.25), so portfolios of two investors will differ if one has a model that captures more information than the other and thus will have projects with lower risk.

Profit depends on solar radiation, which is partly predictable (2.24). Thus, the profit model has two components, a deterministic component (predictive model of the profit) $m(t)_{\bar{u}_m}$ and a completely random component (unpredictable residue of profit) $r_{\bar{u}_m}$ (2.28). This is because solar radiation $\overline{GHR}_m$ is the only random variable in the profit model and because this random variable has a deterministic component (climate model) $m(t)_{\overline{GHR}_m}$ and a completely random residual $r_{\overline{GHR}_m}$(2.26). Next the decomposition of the profit model and how it is affected by the decomposition of solar radiation is shown.

Decomposition of Radiation and Monthly Profit:

$$\overline{GHR}_m = m_{\overline{GHR}_m}(t) + r_{\overline{GHR}_m} \tag{2.26}$$

$$\bar{u}_m = K_m\left(m_{\overline{GHR}_m}(t) + r_{\overline{GHR}_m}\right) - \bar{C}_m \tag{2.27}$$

$$\bar{u}_m = m_{\bar{u}_m}(t) + r_{\bar{u}_m} \tag{2.28}$$

The predictive component associated with climate model $m_{\bar{u}_m}(t)$ incorporates all relevant information held by the investor and will tend to decrease the risk of the project. The variability of the residue $r_{\bar{u}_m}$ is the risk of a project and therefore depends on information not available to the investor.

From the decomposition of the monthly profit (2.26) – (2.28) it can be noticed that as the model becomes more sophisticated, it will tend to explain 100% of the profit. At the limit, if the model $m_{\bar{u}_m}(t)$ has the same expected value than the profit $\bar{u}_m$ then the expected residue is zero $E(r_{\bar{u}_m})$. Moreover, from this decomposition it is intuitive to think that the risk of a project is related to the variability of the residue $r_{\bar{u}_m}$, since risk is present in what is unknown to the investor.

Regarding variabilities, from (2.28) a three-component additive decomposition is possible, relating i) the variability of the monthly profit ii) the variability associated with the model and iii) the variability associated with the residue (the latter variability is associated with risk). Hereinafter risk will be defined as the standard deviation of the residue $r_{\bar{u}_m}$, which in turn is related to the residual variance through $r_{\bar{u}_m}^2$= riesgo^2= $Var(\bar{u}_m)$.

The Variance of monthly profit $\sigma(\bar{u}_m)$ is found applying the variance operator on both sides of the decomposition of the annual profit (2.28) which is equal to the sum of all elements of the covariance matrix between the model $m_{\bar{u}_m}$ and the residue $r_{\bar{u}_m}$.

$$\sigma^2(\bar{u}_m) = [1 \quad 1]\begin{bmatrix} \sigma_m^2 & Cov\binom{m_{\bar{u}_m},}{r_{\bar{u}_m}} \\ Cov\binom{m_{\bar{u}_m},}{r_{\bar{u}_m}} & \sigma_r^2 \end{bmatrix}\begin{bmatrix}1\\1\end{bmatrix} \tag{2.29}$$

$$\sigma^2(\bar{u}_m) = \sigma_m^2 + \sigma_r^2 + 2Cov(m_{\bar{u}_m}, r_{\bar{u}_m}) \tag{2.30}$$

Mathematically *"the covariance of the sum equals the sum of the covariance"* for the monthly profit model. This implies that $Cov(m_{\bar{u}_m},\bar{u}_m{=}m_{\bar{u}_m}{+}r_{\bar{u}_m}) = Cov(m_{\bar{u}_m},m_{\bar{u}_m}) + Cov(m_{\bar{u}_m}, r_{\bar{u}_m})$ and for the residue $Cov(r_{\bar{u}_m},\bar{u}_m{=}m_{\bar{u}_m}{+}r_{\bar{u}_m}) = Cov(r_{\bar{u}_m}, m_{\bar{u}_m}) + Cov(r_{\bar{u}_m},r_{\bar{u}_m})$ as shown below.

$$Cov(m_{\bar{u}_m}, \bar{u}_m) = \sigma_m^2 + Cov(m_{\bar{u}_m}, r_{\bar{u}_m}) \tag{2.31}$$

$$Cov(r_{\bar{u}_m}, \bar{u}_m) = Cov\left(m_{\bar{u}_m}, r_{\bar{u}_m}\right) + \sigma_r^2 \tag{2.32}$$

Conceptually, the variability of monthly profit $\sigma^2(\bar{u}_m)$ is explained by its covariation with the model $Cov(m_{\bar{u}_m}, \bar{u}_m)$ and by its covariation with the residue $Cov(r_{\bar{u}_m}, \bar{u}_m)$. The addition of both covariance equals the variance of the annual profit $\sigma^2(\bar{u}_m)$ as shown below:

Profit Variance Decomposition:

$$\sigma^2(u_m) = Cov\left(m_{\bar{u}_m}, \bar{u}_m\right) + Cov(r_{\bar{u}_m}, \bar{u}_m) \tag{2.33}$$

In matrix form, the covariance between the monthly profit and the model $Cov(m_{\bar{u}_m}, \bar{u}_m)$ is the sum of the components of the first row of the covariance matrix between the model and the residue (2.29). Similarly, the covariance between monthly profit and the residue $Cov(r_{\bar{u}_m}, \bar{u}_m)$ is the sum of the components of the second row of the covariance matrix between the model and the residue (2.29).

In general, the model $m_{\bar{u}_m}(t)$ and the residue $r_{\bar{u}_m}$ do not have the same information, thus it is reasonable to expect a covariance equal to zero $Cov(r_{\bar{u}_m}, m_{\bar{u}_m})$=0. In this case the square of the risk is σ_r^2= $Cov(r_{\bar{u}_m}, \bar{u}_m)$.

Thus, if the investor does not have a model to predict the future radiation, his/her investment risk is equal to the variability of profit. In this case the model of the annual profit is as follows:

No Information Model: $m_{\bar{u}_m}(t) = 0$

$$\rightarrow \sigma(\bar{u}_m) = \sigma_r \qquad (2.34)$$

If the investor has a model proportional to the Global Horizontal Radiation of the type $m_{\bar{u}_m}(t) = K_m \cdot m(t)_{\overline{GHR}_m} - \bar{C}_m$ as presented in the decomposition of the monthly profit (2.26) – (2.28), this would bring new and relevant information to the investor that would allow him/her to predict, at least partly, the variability of the profit (This will reduce the risk to the variability of the difference between the model and the real profit, which is less than the variability of the initially considered profit).

Lineal Model: $m_{u_m}(t) = K_m \cdot\ m(t)_{\overline{GHR}_m} - \bar{C}_m$

$$\rightarrow \sigma_r = K_m \sigma(GHR - m(t)_{\overline{GHR}_m}) \qquad (2.35)$$

At the other extreme, if the model $m_{\bar{u}_m}(t)$ is equal to the actual monthly profit $\bar{u}_m$, the information is complete and the risk is zero because although radiation and plant production changes, these changes are 100% predictable.

Complete Information Model: $m_{\bar{u}_m}(t) = \bar{u}_m$

$$\rightarrow \sigma_r = 0 \qquad (2.36)$$

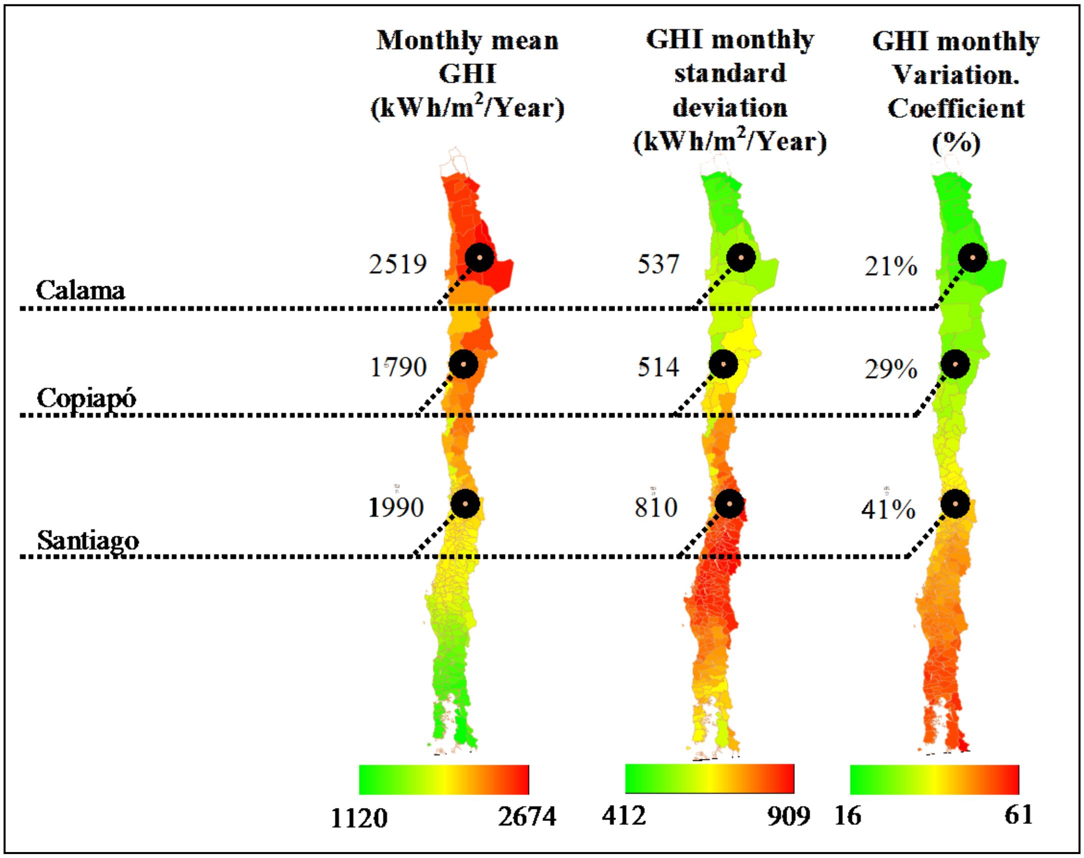

Figure 2-6: Global Horizontal Radiation *GHR* and its variability in Chile.

Prepared with data from the Chilean Solar Energy Explorer (Chile, 2014a).

2.6 Long-term solar resource in Chile

Solar radiation has a strong impact on the profit of a photovoltaic project for both its expected value and its variability, so it is important for investors to know this resource in detail.

In northern Chile, solar radiation is one of the highest in the world with more than 2500 $kWh/year/m^2$ of Horizontal Global Radiation (*GHR*) per square meter in several areas. In Calama, according to the Chilean Ministry of Energy, radiation reaches values as high as 2632 $kWh/year/m^2$ (Chile, 2014a). This radiation decreases towards the south (Figure 2-6) to less than 1120 $kWh/year/m^2$ near Puerto Montt and its variability is greater in the south than in the north, from 412 $kWh/year/m^2$ to 909 $kWh/year/m^2$ for the Standard Deviation σ_{GHR} and from 16% to 61% for the Coefficient of Variation, C_v [10]).

To the south of Concepción σ_{GHR} decreases due to persistent high cloudiness, which explains the low radiation in this geographical area. In northern Chile, far from the sea, the clearest skies in the world can be found[11] and clouds are rarely seen, so variability in PV production is very low. However, in other cities and countries this variation is higher, which makes the model proposed very interesting to be applied elsewhere.

Daily and monthly variability strongly decrease (at least 5 times) for all cities of Chile when aggregated annually. This effect is presented for 10 cities of the country and occurs regardless of the spatial resolution used, compensating the intra-annual seasonal cycles in time for the Coefficient of Variation (Cv) of the Global Radiation Horizontal (GHR) (Figure 2-7). This was done by comparing four different temporal and spatial resolutions: a) High Resolution: 1 km spatial and 1 day temporal (Chile, 2014a); b) Medium Resolution: 1 km spatial and 1 month temporal (Chile, 2014a); c) Low Resolution: 1° lat./long. spatial and 1 month temporal (Stackhouse, n.d.); d) Very Low Resolution: 1° lat./long. spatial and 1 year temporal (Stackhouse, n.d.).

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[10] The Coefficient of Variation is the ratio between the Standard Deviation and the absolute value of the mean (%)
[11] Due to the low clouds Chile hosts the world's largest astronomical development.

Because the variability of the solar resource is compensated over the long term, the investor should be interested in the radiation over the long term (and its direct implication on the profit) considering that its evaluation horizon is usually over 10, 15 or 20 years, not by daily and hourly short-term variability (which tends to be compensated). This means that the model should incorporate annual, inter-annual and seasonal variability of long-term trends that may be due to climate change or inter-decadal climate oscillations. Thus, radiation databases should be of at least a few decades to incorporate these longer term climate phenomena.

However, very few models of solar radiation in the literature include inter-annual impact of ocean-atmospheric oscillations on solar radiation. The models used to predict solar radiation are generally hourly, daily, monthly and intra-annual (seasonal). These essentially consider astronomical effects (extraterrestrial radiation) and atmospheric effects (intra-annual seasonality, clouds, particulate matter, aerosols, transmittance, etc.). Exceptions to this are given in the following section.

When there are very large differences of solar radiation between very close geographic locations, spatial resolution plays an important role, such as in Chile's northern coast. Here, cloudiness is much more intense towards the sea than towards the continent[12].

When radiation data is integrated spatially with lower resolution (such as a resolution of 1° lat./long. versus 1 km^2) these differences generate a greater dispersion and less expected radiation than choosing the alternative with the better resource area. This spatial dependent variation effect is to be appreciated for the Coefficient of Variation

[12] During the night and early morning the sea releases heat accumulated during the previous day which produces steam followed by a coastal fog or low level clouds that tend to dissipate inland.

C_v in the northern ports of Iquique and Antofagasta, and also in Copiapó, where this indicator increases with lower spatial resolution (Figure 2-7). This effect can also be appreciated for the average radiation, which no longer decreases steadily from north to south as is the case for higher resolution radiation (Table 2-1).

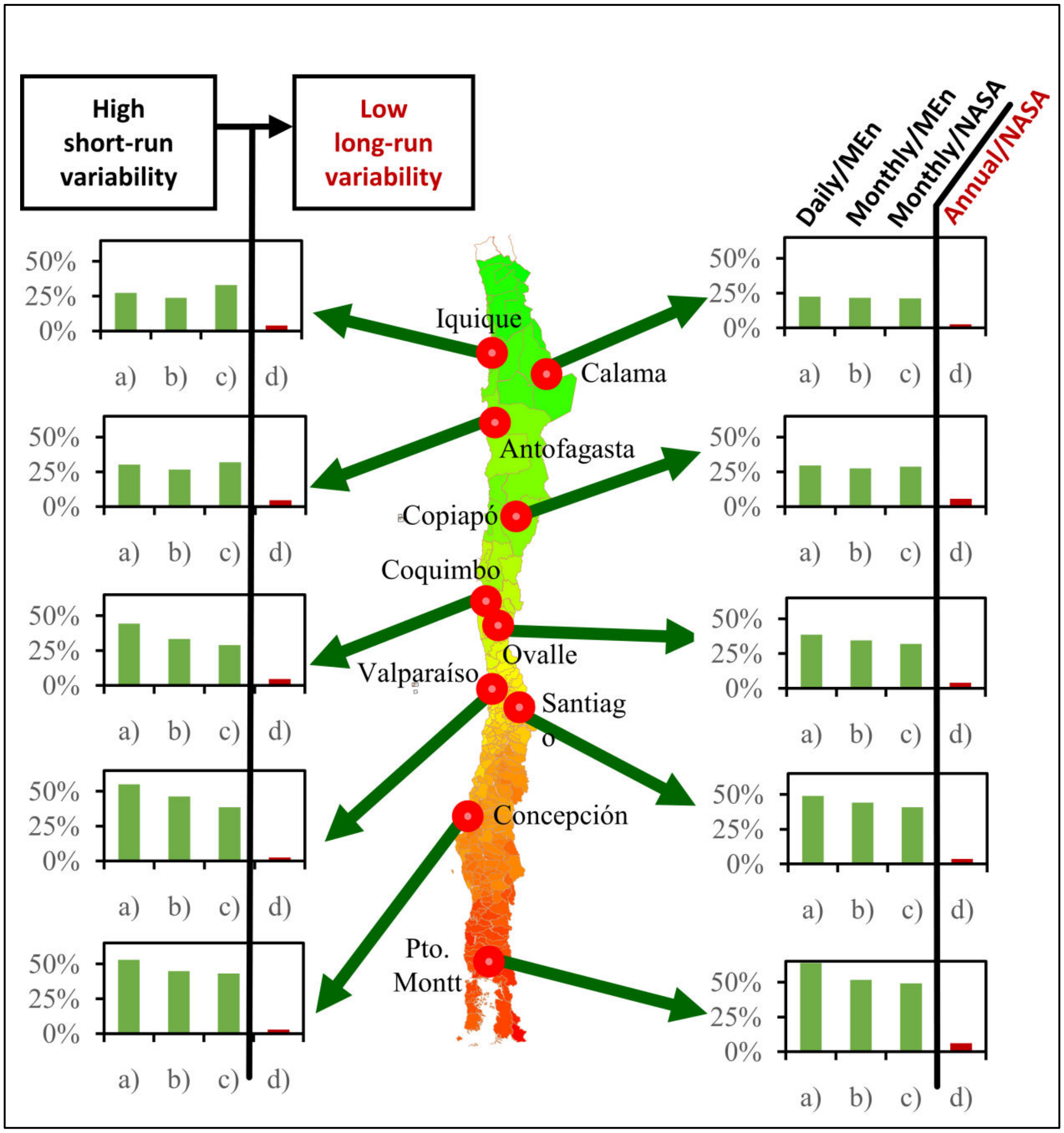


Figure 2-7: Short-run variability in radiation and its compensation in the long-run. The coefficient of variation (C_V) for 10 cities in Chile with different spatial and

temporal resolutions is presented. (a) Daily & 1 km resolution (Chile, 2014a); (b) Monthly & 1 km resolution (Chile, 2014a); (c) Monthly and 1° lat./long. Resolution (Stackhouse, n.d.); (d) Annual & 1° lat./long. resolution (Stackhouse, n.d.).

A database with a long-term horizon was prioritized to study inter-annual variabilities, which have a relevant impact on risk, highlighting the importance of long term for investors, despite the side effect of low spatial resolution. Thus, due to the greater time horizon (*NASA*: 22 years; Ministry: 10 years) radiation data from *NASA* (Stackhouse, n.d.) was used for this study instead of the Chilean Ministry of Energy's solar database (Chile, 2014a). This, despite the fact that the database of the Ministry has greater spatial and temporal resolution (*NASA*: 1º lat./long. and 1 month; Ministry: 1 km^2 and 30 min.).

2.7 Ocean-atmospheric oscillations

Given the importance for the PV investor to model the long-term variations of solar radiation (as the variability of solar radiation of short term tends to be compensated in the long-run) it is relevant to study climatic phenomena affecting solar radiation in inter-annual periods.

Climatologically, inter-annual deviations from the mean value are called climate anomalies. A large influence over inter-annual climate anomalies are driven by the so-called Climate Oscillations. Less influential and of longer-term are the inter-decadal climate oscillations and the climate change. This latter phenomenon is very important both for the scientific community and for the civil community due to potential social, environmental and economic impacts on a planetary scale.

2.7.1 Impact on climate

Ocean-atmospheric Oscillations are climatic cycles with variable periodicity which affect certain regions of the planet earth. These cause annual climate anomalies (deviations from expected weather). There are many ocean-atmospheric oscillations located in different ocean basins and not all are well understood. In some cases doubts arise if they only are random walks (Stephenson, Pavan, & Bojariu, 2000).

The best known ocean-atmospheric oscillation is El Niño Southern Oscillation (*ENSO*), which affects the whole basin of the Pacific Ocean and has been found responsible for various disasters such as floods, droughts and forest fires (Cane, 2005). Moreover, studies showing the impact of *ENSO* globally, beyond the Pacific Ocean (Halpert & Ropelewski, 1992; C F_ Ropelewski & Halpert, 1989), are abundant in literature.

In addition to *ENSO* and particularly in the south-east coast of South America, according to González (M. H. González & Vera, 2010), ocean-atmospheric oscillations that affect climate are: i) the Southern Annular Mode (*SAM*) which is related to the Southern Ocean basin (around the Antarctic) and ii) the Indian Ocean Dipole (*IOD*) which is related to the Indian Ocean basin. It should be noted that the study of González is related to rainfall and not to solar radiation[13].

[13] For this area there are no studies associating the impact of climate oscillations with solar radiation

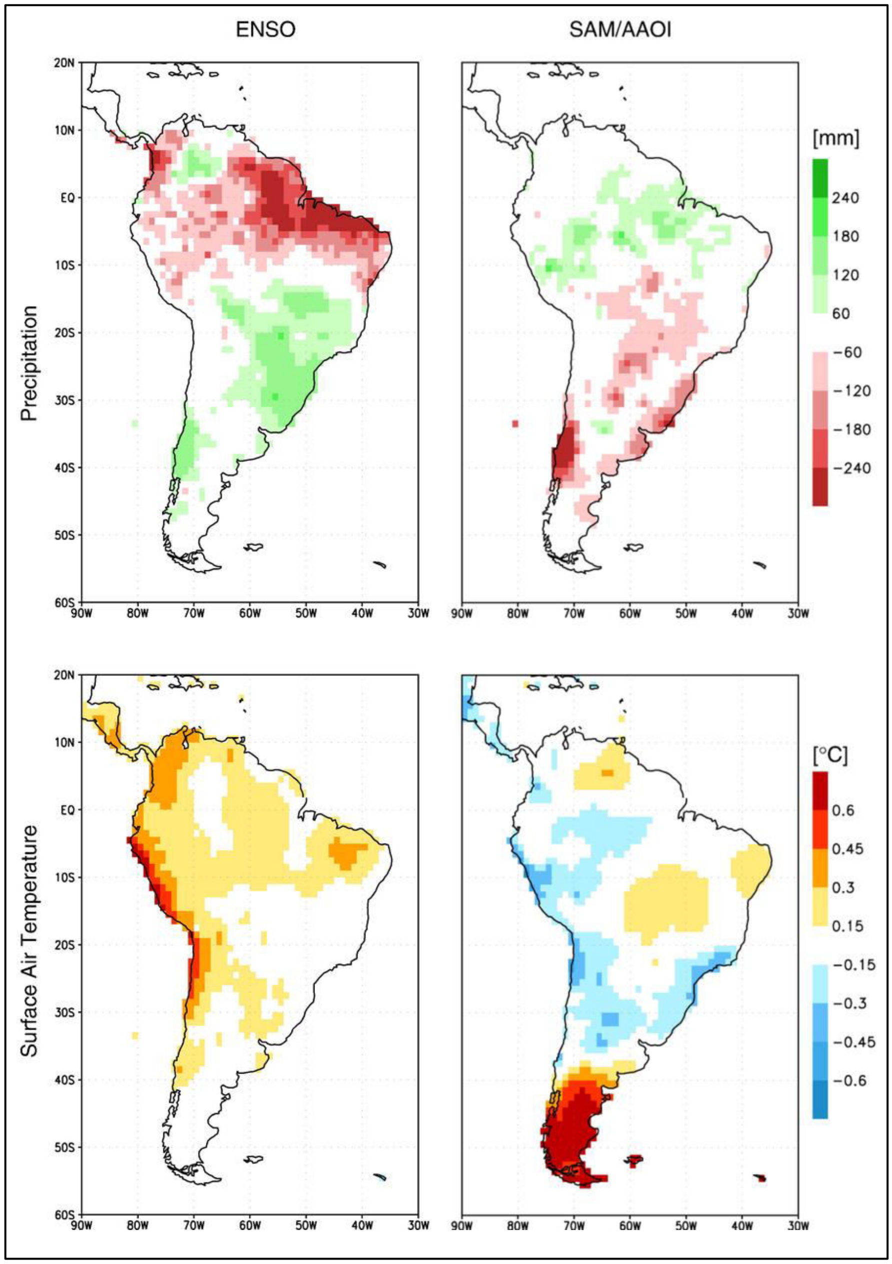


Figure 2-8: Climate Impact on South America of *ENSO* and *SAM* on precipitation and temperature: Expressed per unit of *MEI* and *SAMI* indexes for each ocean-atmospheric oscillation respectively. Rainfall increases in the north-east and decreases in the south. Temperature rises especially in Peru and northern Chile (Garreaud, Vuille, Compagnucci, & Marengo, 2009).

The ocean-atmospheric oscillations such as *ENSO*, *IOD* and *SAM* significantly influence precipitation, atmospheric temperatures, wind, sea surface temperature and global or regional atmospheric pressures. According to Garreaud (Garreaud et al., 2009), *ENSO* and *SAM* affect rainfall and ambient temperature in South America (Figure 2-8). Garreaud shows how ambient temperature and rainfall are affected by an additional unit of i) the Multivariate *ENSO* Index (*MEI*) associated with *ENSO* and ii) the *SAM* Index (*SAMI*) associated with *SAM*. Both indexes are explained later in the next subsection. Precipitation increases from about 120 to -240 mm/year for both indexes, but with opposing locations. *SAM* (*ENSO*) increases (decreases) precipitation in the north and decreases (increases) in the south. Temperature moves between 0°C and 0.6°C for *ENSO* and between -0.6ºC and 0.6°C for *SAM*. In general, *ENSO* index does not decrease temperatures. Additionally it increases temperature in the locations where the *SAM* index decreases them. A notable exception is the Patagonia, where *SAM* has a strong positive influence. The influence of *ENSO* on Peru and northern Chile, where the temperature rise peaks (reaching 0.6°C) is also highlighted.

2.7.2 Ocean-atmospheric oscillations in Chile

The 3 most important ocean-atmospheric oscillations for Chile (*ENSO*, *IOD* and *SAM*) have important implications for hydroelectric, wind and solar generation. These largely determine the long-term climatic variations and therefore the availability of the primary energy resource.

The ocean-atmospheric oscillations studied have a monopole type behavior (in a fixed geographical area) or a dipole type behavior (between two fixed geographical areas) with respect to the climate mean depending on the variable measured. The most typical variables are the Sea Surface Temperature (*SST*) and Sea Level Pressure (*SLP*). For example, the behavior of *ENSO* using *SST* is of the monopole type, oscillating in the geographical area "El Niño 3.4" from maximum to minimum deviation with respect to average temperature. Moreover, using *SLP*, *ENSO's* behavior is of the dipole type between the measuring stations of Tahiti and Darwin, alternating their maximum and minimum deviations between stations. Both behaviors represent the evolution of the same oscillation by measuring different variables. These oscillations are described briefly below.

2.7.3 El Niño Southern Oscillation (*ENSO*)

ENSO is a climate phenomenon that is based on a coupled system between atmosphere and ocean with irregular intervals of 2-7 years between its warm phase (El Niño) and its cold phase (La Niña) (Cane, 2005). It is characterized by the use of different indexes among which the most popular are Ocean El Niño Index (*ONI*), Southern Oscillation Index (*SOI*) and Multivariate *ENSO* Index (*MEI*). These ratios are described below:

a) Ocean El Niño Index (*ONI*)

ONI is the deviation of the sea surface temperature (*SST*) in a specific area of the Equatorial Pacific called Niño 3.4 (between longitudes 120 and 170ºW and between latitudes 5°N and 5°S). When the deviation is above (below) 0.5ºC *ENSO* is in El Niño (La Niña) phase (National Weather Center, 2015).

b) Southern Oscillation Index (*SOI*)

SOI is an index that measures the standardized difference of the atmospheric pressure at sea level (*SLP*) between weather stations in Darwin (Australia) and in Tahiti (French Polynesia). When *SOI* is negative (positive) then *ENSO* is in the phase El Niño (La Niña) ("ENSO Wrap-Up, Southern Oscillation Index," 2015; National Weather Service, 2015).

c) Multivariate ENSO Index (*MEI*)

MEI is an index that combines atmospheric sea level pressure (*SLP*), zonal and meridional components of the surface wind, sea surface temperature (*SST*), air temperature on the surface and Cloudiness Fraction of the sky. These variables are filtered through clustering and their first principal component is taken without rotation (Earth System Research Laboratory, 2015).

2.7.4 Southern Annular Mode (*SAM*)

Southern Annular Mode (*SAM*), also known as Antarctic Oscillation (*AAO*), describes the movement from north to south of westerly winds belt which surrounds Antarctica, dominating mid- to high latitudes of the southern hemisphere. Its index is the SAM Index (*SAMI*) and is defined as the difference between the normalized sea level pressure (*SLP*) between 40°S and 70°S latitudes (Nan & Li, 2003). In its positive (negative) phase the belt of westerly winds contracts to (expands away from) the Antarctic (J. Li, n.d.; "Southern Annular Mode," 2015).

2.7.5 Indian Ocean Dipole (*IOD*)

Indian Ocean Dipole (*IOD*) is a coupled ocean-atmospheric phenomenon in the Indian Ocean Ecuador. Its index is the Dipole Mode Index (*DMI*), which is calculated from the difference in ocean surface temperatures (*SST*) between western (50º to 70ºE and 10ºN to 10ºS) and eastern areas (90º to 110ºE and 10ºS to 0ºS). Phase is positive (negative) when *SST* is warmer (colder) than normal in the west and cooler (warmer) in the east ("Indian Ocean," 2015).

2.7.6 Dynamics of ocean-atmospheric oscillations and its influence on the solar Resource

Ocean-atmospheric oscillations that affect climate in the west coast of South America move mass and energy in the Pacific, Indian, and Antarctic Oceans as well as with the atmosphere. These oscillations are interrelated and impact solar resource, affecting the risk of a photovoltaic project in the long term.

Pacific Ocean's basin is the world's largest, and *El Niño Southern Oscillation* (*ENSO*) is the most important ocean-atmospheric oscillation that develops in it. Its dynamic is the most studied because of its size and influence but is far from being fully understood (Halpert & Ropelewski, 1992; C F_ Ropelewski & Halpert, 1989). This influence should be considered when developing a photovoltaic plant and depends on the speed of propagation of the warm (*El Niño*) and the cold phase (*La Niña*), as well as on the geographic location in which the plant will be installed.

Of the various natural phenomena that explain the dynamic evolution of *ENSO* (in theoretical models currently discussed in the literature), the Kelvin and Rossby waves are highlighted. Kelvin waves play an important role in the positive feedback of the warm phase of *ENSO* (*El Niño*). By contrast, Rossby waves play an important role in theories that explain the negative feedback of this phase, returning the balance to the neutral or cold phase (the latter called *La Niña*). For a review of the theories that seek to explain the dynamics of *ENSO* see (C. Wang, Deser, Yu, DiNezio, & Clement, 2012).

Kelvin Waves are oceanic and atmospheric waves that occur in the Equator or along the coasts. In the Ecuador, Kelvin Waves are oceanic and move only eastward with a typical speed of 2.8 m/s (cross the Pacific Ocean in 2 months) due to the waveguide effect that takes place because of the lack of Coriolis force at this latitude. Kelvin Waves that propagate along the coast (which are trapped by their neighborhood) always move with the coastline towards the right in the northern hemisphere and to the left in the southern hemisphere (cyclonic rotation direction). Its propagation speed is typically 2m/s (Gill, 1982; B. Wang, 2002))

Rossby waves are oceanic or atmospheric waves that always move westward at speeds of 1-50 cm/s, which means they can take years to cross the basin (Chelton, Dudley (Oregon State University & Schlax, Michael (Oregon State University, 1996). They are produced in geographical areas where an anticyclone is located toward the pole (vortex with high pressure center and anti-clockwise rotation in the southern hemisphere) and a cyclone is located toward the Equator (vortex low pressure center and clockwise rotation in the southern hemisphere). Rossby waves are caused by the Coriolis force (which is produced due to the rotation of the earth) and by the spherical shape of the earth. Coriolis forces do not affect the objects in the direction parallel to the axis of the earth. Considering water columns at sea that are parallel to the axis of rotation, these water columns will be shortest in the Pole and longest in the Equator. Thus, a column located at a given latitude that moves towards the pole will be squeezed (because it has to reduce its length) generating an area of higher pressure than its surroundings and therefore an anticyclonic movement. Similarly, if the column moves towards the Equator it will expand producing a low pressure zone and a cyclonic motion. When both effects occur (anticyclone toward the Pole and cyclone toward the Equator) we are in presence of a Rossby Wave.

Oceanic Rossby waves may occur due to reflection of Kelvin waves on the continent, while atmospheric Rossby waves are found in the convergence zones (*Intertropical Convergence Zone* - *ITCZ* or subtropical convergence zone where the polar easterlies join with the prevailing westerlies) (J R Holton, 2003).

In summary, Kelvin and Rossby Waves play an important role in the influence ocean-atmospheric oscillations will have on solar radiation in the long term. This influence will depend on the speed of propagation of these waves, which contribute to changes in phase (from *El Niño* to *La Niña*), and on oscillations' delay to affect a particular geographic location (from months to several years). For example, for *ENSO*, Kevin waves take approx. 2 months to cross the Pacific Ocean from west to east and contribute in the development of its warm phase. By contrast, Rossby waves can take several years to cross from east to west and according to some theories allow the change to the cold phase.

2.8 Profit models with prediction due to climate information

To quantify the impact of reducing the risk on a photovoltaic investment using a long-term profit model that includes solar radiation and ocean-atmospheric oscillations, 3 models were compared with different levels of complexity and information (Figure 2-9): a) Standard methodology used by the industry (simply mean and variance of profit); b) Cyclic Model (annual seasonality and long-term trend of solar radiation); c) Complex Model (equal to the Cyclic Model, but adding ocean-atmospheric models).

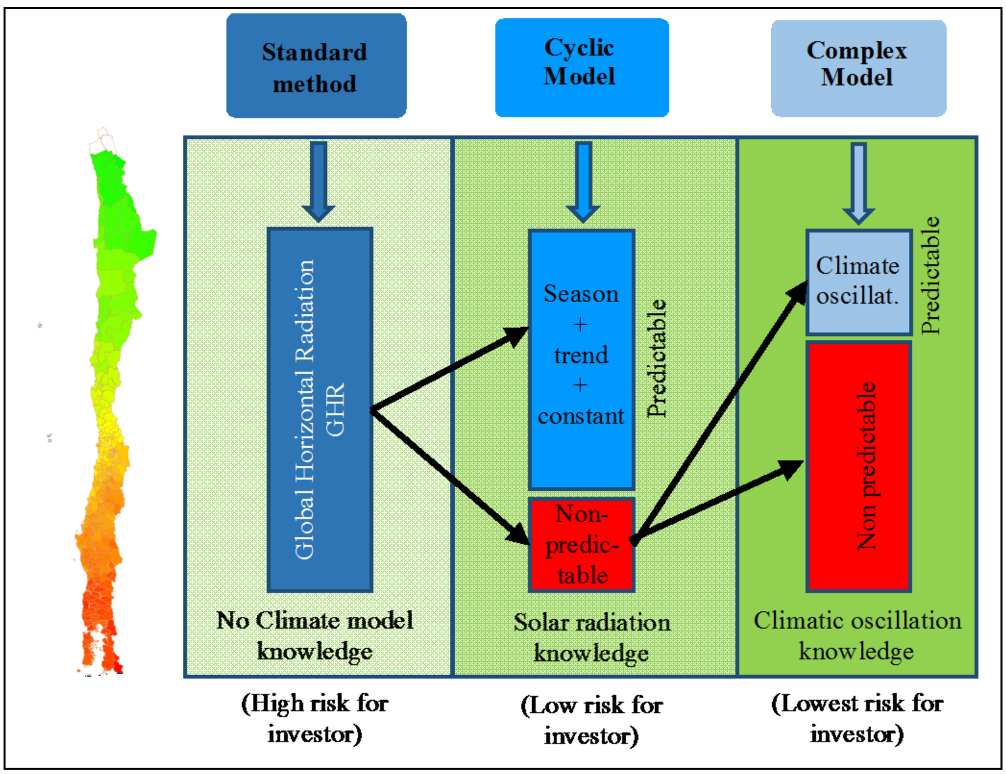


Figure 2-9: Risk reduction scheme according to the proposed models. a) Standard method (only standard deviation); b) Cyclic Model; c) Complex Model. The variability of the solar resource affects the risk of the project depending on the information (knowledge) available to the investor.

The Standard methodology is one where the investor has no model as such for changes in its profits and, therefore, faces risk simply in a statistical way. That is, it models the monthly expected profit and risk with the mean and variance. Cyclic Model should reduce the risk of investment with respect to the standard methodology because of the information implicit in past solar radiation, particularly through its representation of periodic cycles and trends. Similarly, the Complex Model should further reduce risk with respect to the Cyclic Model, due to the information delivered by the ocean-atmospheric oscillations, because precisely these - not entirely periodic - oscillations would explain much of the inter-annual profit changes.

Therefore, project risk depends on the information (knowledge) available to investors in relation to the radiation and climate in the geographic location of the plant.

Each of the models used are presented in detail below.

2.8.1 Cyclic Model (seasonality and trend of solar radiation)

The Cyclic Model makes a simple, fast and conventional approach of profit, using the information contained in the Global Horizontal Radiation (*GHR*) with monthly resolution, without considering ocean-atmospheric oscillations.

To this purpose, *GHR* is decomposed into an intra-annual cyclical seasonality, a long-term trend and a constant. The decomposition is incorporated in the model of the daily mean monthly profit $m_{\bar{u}_m}(t)$ explained previously in subsection *2.3. Risk structure and profit model*. Thus, similarly to *GHR*, daily mean monthly profit for the Cyclic Model $m_{cy,\bar{u}_m}(t)$ is also decomposed into an intra-annual cyclical seasonality

Acos(2πt/P-θ), a linear trend *Tt* and a constant *C*. The trend represents the influence of Climate Change or of very long-term ocean-atmospheric oscillations. The latter corresponds to climate anomalies with periodicities of decades, larger than the measurements used (20 years). The annual seasonality is determined by the intra-annual cycle of solar radiation and is characterized by a cosine with a 12 months period (*P=12*) in phase θ with the extraterrestrial radiation G_o, and therefore with a maximum in December.

To determine the influence of each component the following coefficients shall be calculated: i) *A* of seasonality, ii) *T* of trend and iii) *C* of constant. This was performed using a linear regression that minimizes the mean square error (*OLS*). Thus, the Cyclic Model for the profit is expressed as follows:

$$m_{cy,\bar{u}_m}(t) = C + Tt + \mathrm{A}\cos((2\pi/P)t - \theta) \qquad (2.37)$$

2.8.2 Complex Model (with climate anomalies)

The Complex Model builds on the previous model based on solar radiation's seasonality and trend (Model Cyclic) adding the information contained in the 3 most important ocean-atmospheric oscillations in Chile (*ENSO*, *IOD* and *SAM*) through 3 instrumental variables (VI_{ONI}, IV_{SAMI} and VI_{DMI} respectively) (2.38) - (2.39). The influence of each ocean-atmospheric oscillation on the geographical location of the plant depends on the evolution of the oscillation and on the location of the plant. The evolution of the oscillation is characterized by an index measuring one or several climatic variables (e.g., *ONI* is determined by measuring the sea surface temperature *SST* in the Niño 3.4 region and characterizes *ENSO*) and depends on the internal dynamics of the oscillation (for example due to Kelvin and Rossby Waves). The geographical location determines specifically the intensity with which each oscillation affects solar radiation (Davy & Troccoli, 2012; Pozo-Vázquez et al., 2004; Prasad et al., 2015).

To determine how the evolution of each ocean-atmospheric oscillation impacts on radiation and profit in a specific location, an autoregressive *AR* model for each of the 3 indexes (*ONI*, *SAMI* and *DMI*) was developed (2.40) - (2.42). Each *AR* model is equal to the weighted sum of the lags up to p_o *for ENSO*, p_s for *SAM* and p_d for *IOD*. Therefore, the daily mean monthly profit of the Complex Model $m_{co,\bar{u}_m}(t)$ (2.38) - (2.42) is decomposed into: i) 3 components, each related to one oscillation; ii) a cyclical intra-annual seasonality $A\cos(2\pi t/P-\theta)$[14], iii) a trend Tt and iv) a constant C.

$$m_{co,\bar{u}_m}(t) = C + Tt + A\cos((2\pi t/P) - \theta) + IV(t) \quad (2.38)$$

$$IV(t) = IV_{ONI}(t) + IV_{SAMI}(t) + IV_{DMI}(t) \quad (2.39)$$

$$IV_{ONI}(t) = \sum_{j=1}^{p_o} B_{j,o}\, ONI_{t-j} \quad (2.40)$$

$$IV_{SAMI}(t) = \sum_{j=1}^{p_s} B_{j,s}\, SAMI_{t-j} \quad (2.41)$$

$$IV_{DMI}(t) = \sum_{j=1}^{p_d} B_{j,d}\, DMI_{t-j} \quad (2.42)$$

To determine the influence of each component in the daily mean monthly profit $m_{co,\bar{u}_m}(t)$ coefficients $B_{j,o}$ of *ENSO*, $B_{j,s}$ of *SAM*, $B_{j,d}$ of *IOD*, A of seasonality, T of trend and C of constant were calculated using a linear regression that minimizes the mean square error (*OLS*).

[14] The annual seasonality is characterized by a cosine with period of 12 months (P = 12) and phase θ equal to that of extraterrestrial radiation G_o (maximum in December).

2.8.3 Model for ocean-atmospheric oscillations

To determine the effect of an ocean-atmospheric oscillation at a given location using the Complex Model the maximum number of lags that could predict its own evolution must be estimated first (p_o, p_s and p_d for *ONI*, *SAMI* and *DMI* respectively). For this purpose a family of autoregressive AR models was fitted to each oscillation's index ($\widehat{ONI}_t$, $\widehat{SAMI}_t, \widehat{DMI}_t$) (2.43) – (2.45), testing all lags from 1 to 20 months. To choose the best model that avoids over-fit or loss of information the smallest lag was chosen between the Akaike Information Criteria (*AIC*) (Akaike, 1974) and the Bayesian Information Criteria (*BIC*) (Schwarz, 1978). In addition, to validate the application of *AR* models (Box, Jenkins, & Reinsel, 2008) stationarity was checked (no unit roots) using the *Augmented Dickey Fuller* test (*ADF*) (Said & Dickey, 1984). The *AR* models for each of the ocean-atmospheric oscillations are presented below, where a_o, a_s, a_d, $b_{j,o}$, $b_{j,s}$, $b_{j,d}$, c_o, c_s, c_d, d_o, d_s and d_d are parameters determined by an Ordinary Least Square Regression (*OLS*).

$$\widehat{ONI}_t = c_o + d_o t + a_o ONI_{t-1} + \sum_{j=1}^{p_o} b_{j,o}\, \Delta ONI_{t-j} \tag{2.43}$$

$$\widehat{SAMI}_t = c_s + d_s t + a_s SAMI_{t-1} + \sum_{j=1}^{p_s} b_{j,s}\, \Delta SAMI_{t-j} \tag{2.44}$$

$$\widehat{DMI}_t = c_d + d_d t + a_d DMI_{t-1} + \sum_{j=1}^{p_d} b_{j,d}\, \Delta DMI_{t-j} \tag{2.45}$$

The fit of the autoregressive models (*AR*) for each of the indexes (*ONI*, *SAMI* and *DMI*) is very good ($R^2 > 0.92$) (Table 2-2 and Figure 2-10). Lags obtained were p_{ONI}=8, p_{SAMI}=14 and p_{DMI}=17, with R^2 = 99.1%, R^2 = 92.5% and R^2 = 96.1% respectively. That is, to reproduce the time series with this method as close as possible delays of 8 months for *ONI*, 14 months for *SAMI* and 17 months for *DMI* are enough.

Table 2-2: Fit & validation of ocean-atmospheric oscillation models. Developed using autoregressive models for *ONI*, *SAMI* y *DMI*.

Ocean-atmospheric Oscillation	ENSO	SAM	IOD
Index	ONI	SAMI	DMI
Total Observation Period	Jan 1900 – Dec 2013	Jan 1957 – Dec 2014	Jan 1958 – Dec 2010
Model Fit Period	Jan 1900 – Dec 1956	Jan 1957 – Dec 1982	Jan 1958 – Dec 1983
Model Validation Period	Jan-1957 – Dec 2013	Jan-1983 – Dec 2014	Jan-1984 – Dec 2010
Lags AR Model	7	14	17
R^2	98.4%	93.5%	96.9%
Adjusted R^2	98.4%	93.1%	96.7%

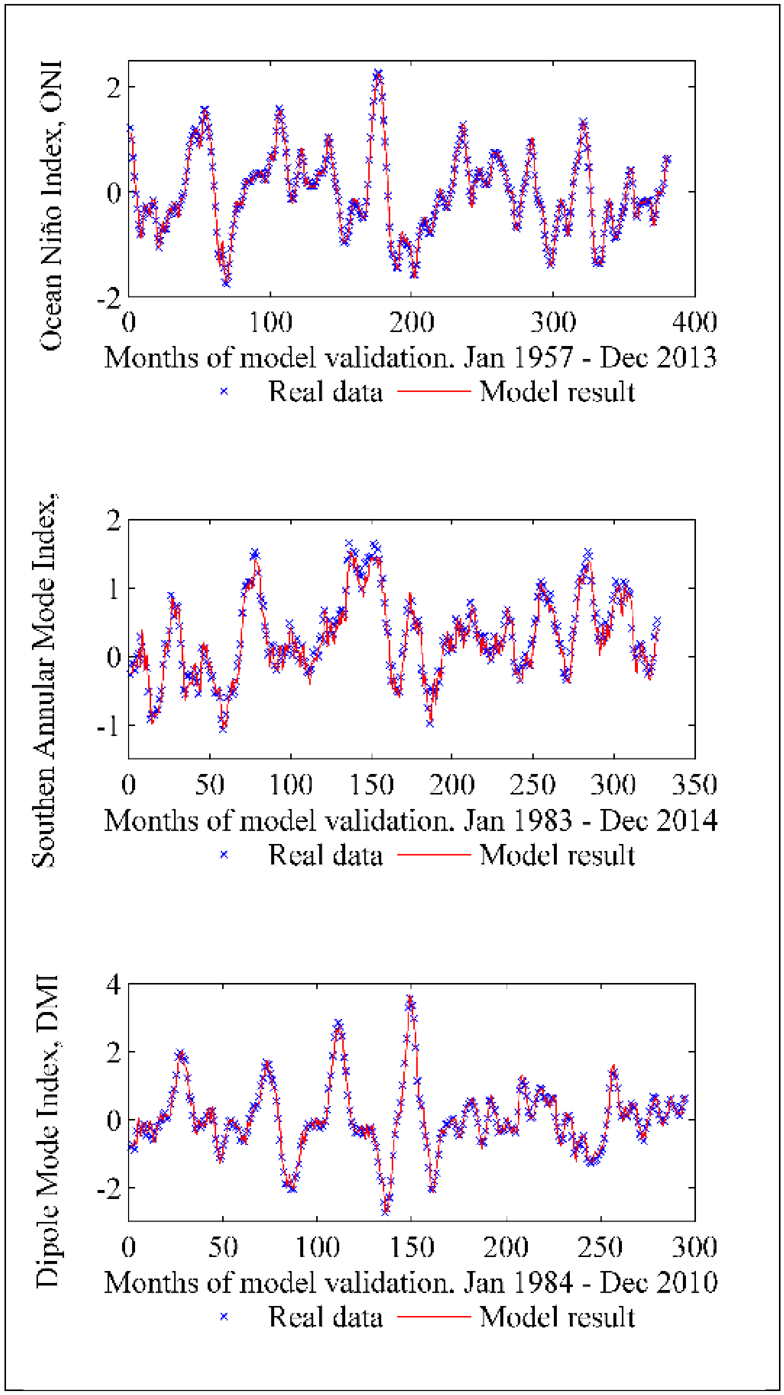


Figure 2-10: Model fit for *ENSO*, *SAM* and *IOD* ocean-atmospheric oscillations.

2.8.4 Data sources of radiation, ambient temperature, and indexes of ocean-atmospheric oscillations

For the Global Horizontal Radiation (*GHR*) the available data from the *NASA Surface Meteorology and Solar Energy* database was used, which have a spatial resolution of 1° latitude and 1º longitude, a temporal resolution of one month and covers the years 1984-2005 (Stackhouse, n.d.). From this source, with the same temporal resolution and time span as *GHR*, the ambient temperature was obtained which is essential to calculate the efficiency of photovoltaic modules (Table 2-3). This data source was chosen over the one published by the Chilean Ministry of Energy (Chile, 2014a) because it covers a greater time span (NASA: 20 years; Ministry: 10 years), which enables the incorporating of various periods of the ocean-atmospheric oscillations, despite having lower spatial and temporal resolution.

For *ONI* associated with *El Niño Southern Oscillation* (*ENSO*) data between 1950 and 2012 published by the *NOAA* (National Weather Center, 2015) was used. For *SAMI* associated with *Southern Annular Mode* (*SAM*) data 1957-2014 published by *British Antarctic Survey* (G. Marshall, 2015) was used. Also, for *DMI* associated with the *Indian Ocean Dipole* (*DMI*) data between 1958 and 2010 published by *Japan Agency for Marine-Earth Science and Technology* ("Dipole Mode Index (DMI)," n.d.) was used (Table 2-3). Data associated with these oscillations has a 1 month resolution.

Table 2-3: Time series sources of meteorological variables. Time range and resolution.

Serie	Time Range (Years)	Resolution	Data Source
GHR	1984-2005	1º (Lat, Long) & 1month	NASA[a]
Ambient Temperature	1984-2005	1º (Lat, Long) & 1 month	NASA[a]
ONI	1950-2012	---	NOAA[b]
SAMI	1957-2014	---	British Antarctic Survey[c]
DMI	1958-2010	---	JAMSTEC[d]

[a] NASA Surface Meteorology and Solar Energy (Stackhouse, n.d.)

[b] National Oceanic and Atmospheric Administration (National Weather Center, 2015)

[c] (G. Marshall, 2015)

[d] Japan Agency for Marine-Earth Science and technology (“Dipole Mode Index (DMI),” n.d.)

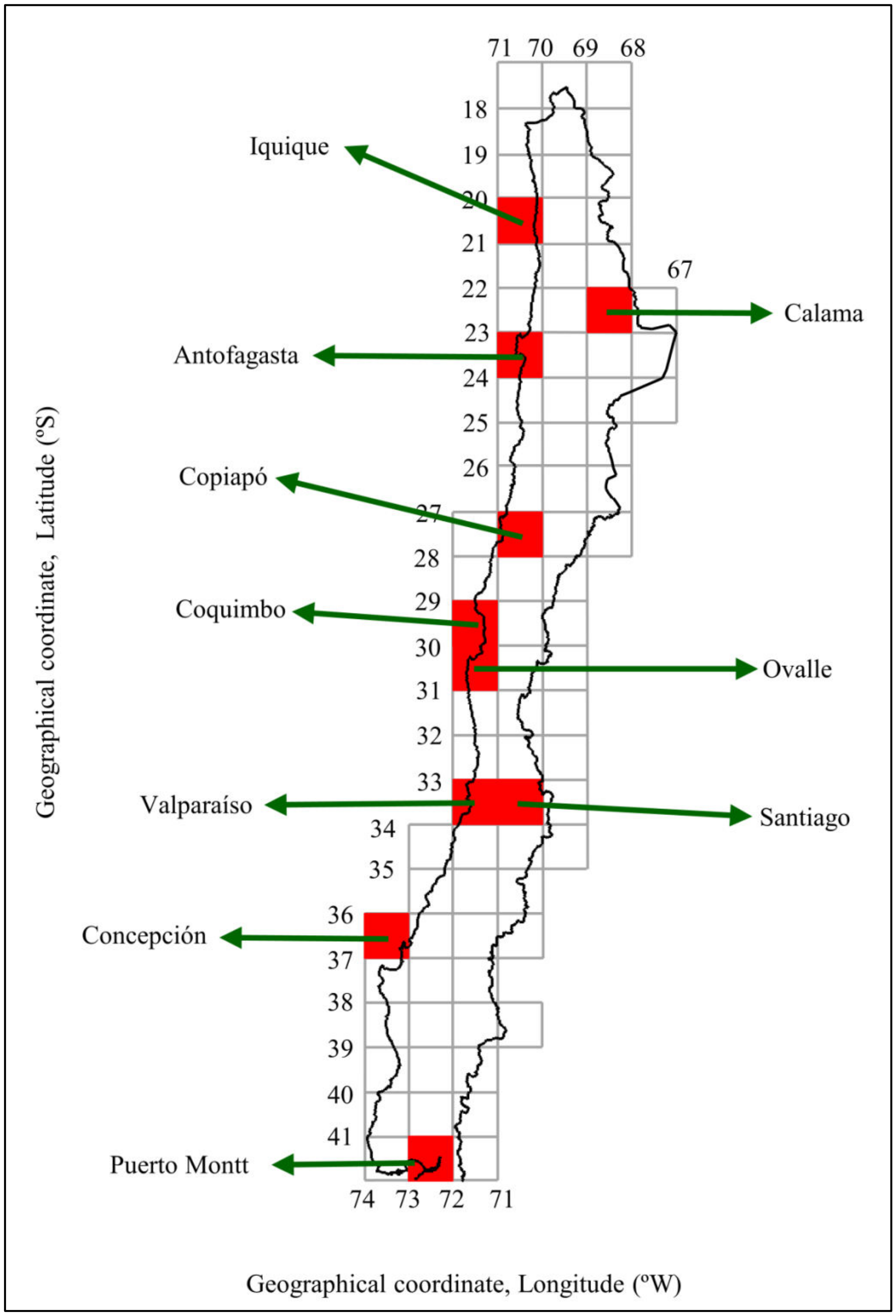


Figure 2-11: Map of Chile with 10 geographical areas studied (1º lat./long.). Each area is marked with the name of its most important city.

2.9 Results: Risk reduction

The variability of the monthly profit for a typical PV project located in 10 geographical areas of Chile is presented in this section. The size of these areas is 1º lat./long., distributed from north to south and identified with the name of its most relevant city (Figue 2-12). For this purpose, two monthly profit models with different levels of complexity are developed to reduce investor risk (2.37) – (2.42): i) The Complex Model that predicts ocean-atmospheric oscillations (*ENSO*, *SAM* and *IOD*), seasonality and trend of solar radiation (2.38) - (2.42) and ii) the Cyclic Model that predicts only seasonality and trend (2.37). The oscillations and the trend partly explain the inter-annual variability (long term) and seasonality explains the intra-annual (medium term) variability.

In Chile, a 100 *MW* photovoltaic project could reduce its risk to very low levels, ranging from 1.11 to 2.38 *MMUSD*/year for the 10 geographical areas using the Complex Model (predicting ocean-atmospheric oscillations, seasonality and trend). This model achieves a risk between 6% and 13% lower than the simpler Cyclic Model (only seasonality and trend) (Figure 2-12), whose risk ranges from 1.20 to 2.55 *MMUSD*/year. With the standard methodology (without a predictive model) the risk is much higher, ranging from 4.93 to 7.88 *MMUSD*/year (Table 2-4). This risk is calculated simply as the standard deviation of monthly profit over a period of 20 years (standard case). Thus, Cyclic Model represents a dramatic reduction, from 57% to 79%, for the 10 geographical areas with respect to the standard methodology (Figure 2-13).

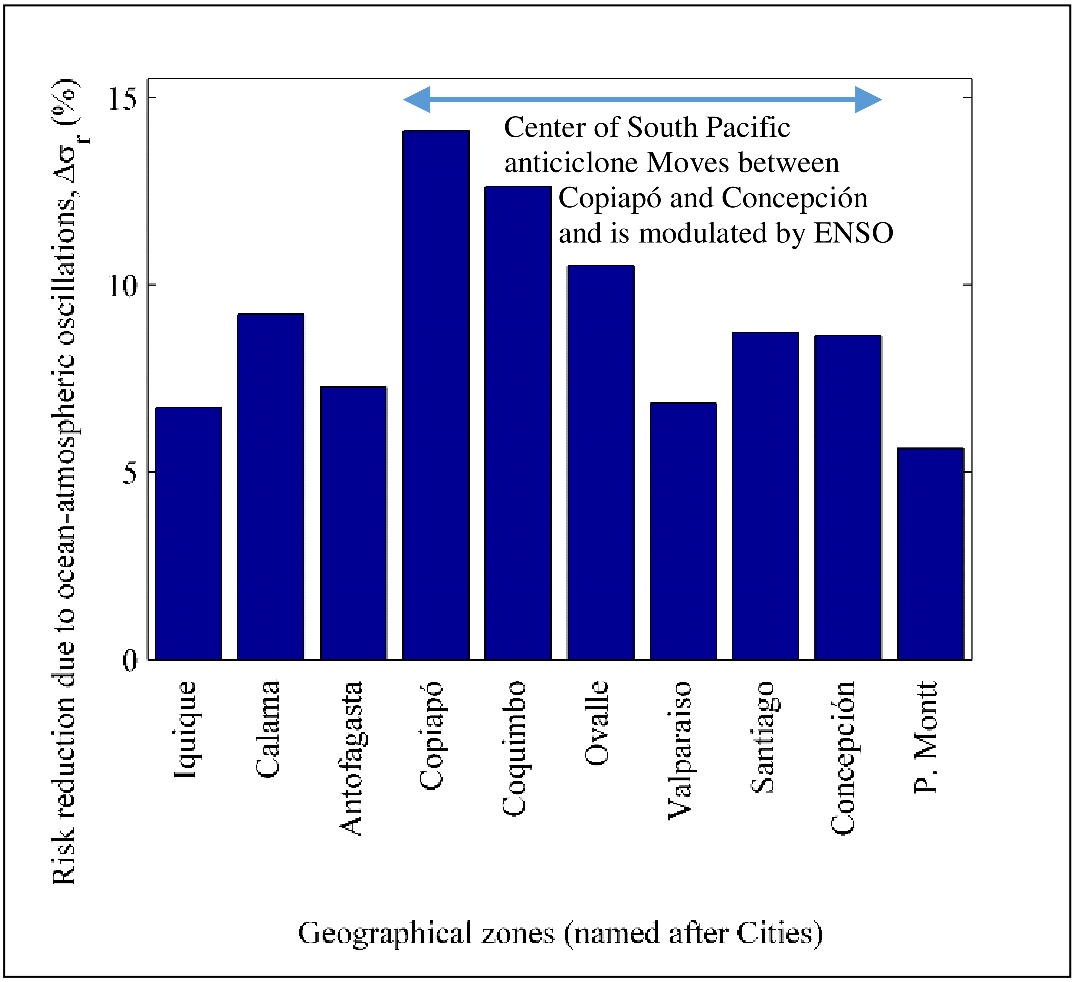


Figure 2-12: Residual variance reduction due to oscillations (%).

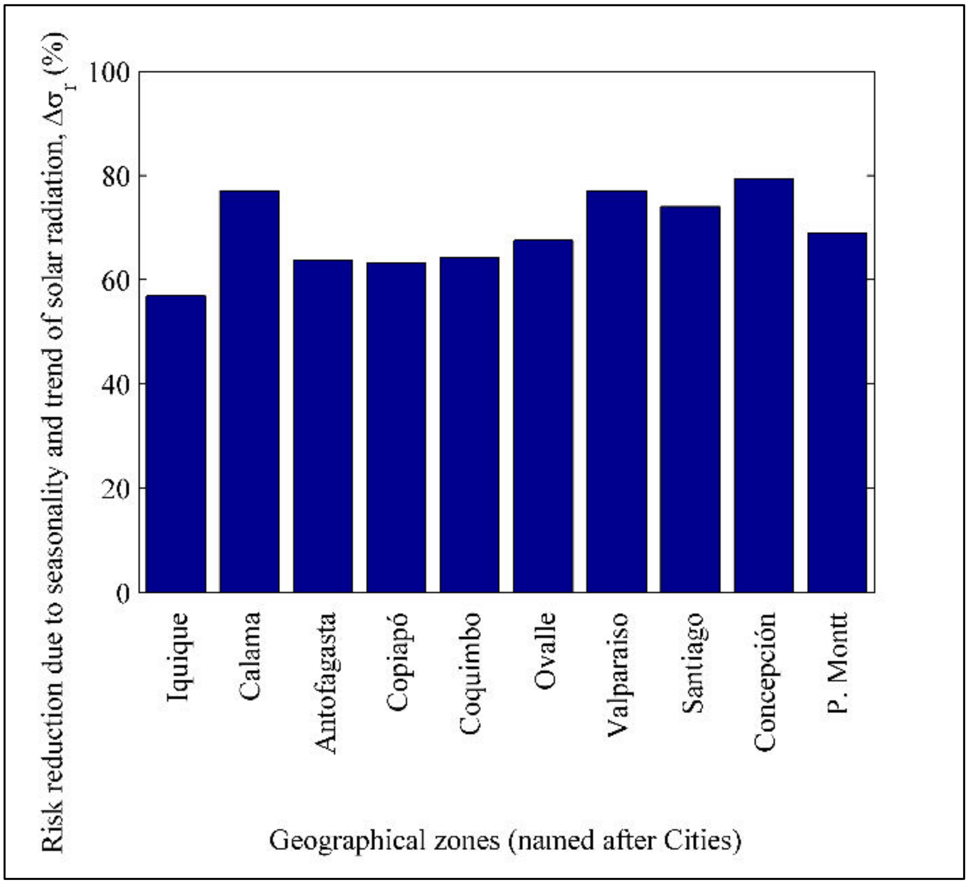


Figure 2-13: Residual variance reduction due to solar radiation (seasonality and trend).

The proposed methodology reduces investor's risk between 60% and 81% over the standard methodology. This is a substantial improvement to the mainstream financial risk assessment on *PV* projects. Financial institutions usually assess the risk of a PV project through the use of percentiles *P90*, *P95* and/or *P99* of a typical meteorological year *TMY*, which essentially represent deviations from the typical average year (*P50*) (Cebecauer & Suri, 2015). This paper corrects the above through predicting climate behavior, resulting in more accurate risk assessments that should improve the bankability of PV projects.

Seasonality (cycle with maximum in December and a 12-month period) is the component that explains most of the reduction in risk, accounting for between 81% and 96% of the variance of profit for both models (Figure 2-14 and 2-15). This component is highly predictable and if accounted for, allows the analysis of the remaining inter-annual variations, which finally determine the "true" project risk (for a constant selling energy price).

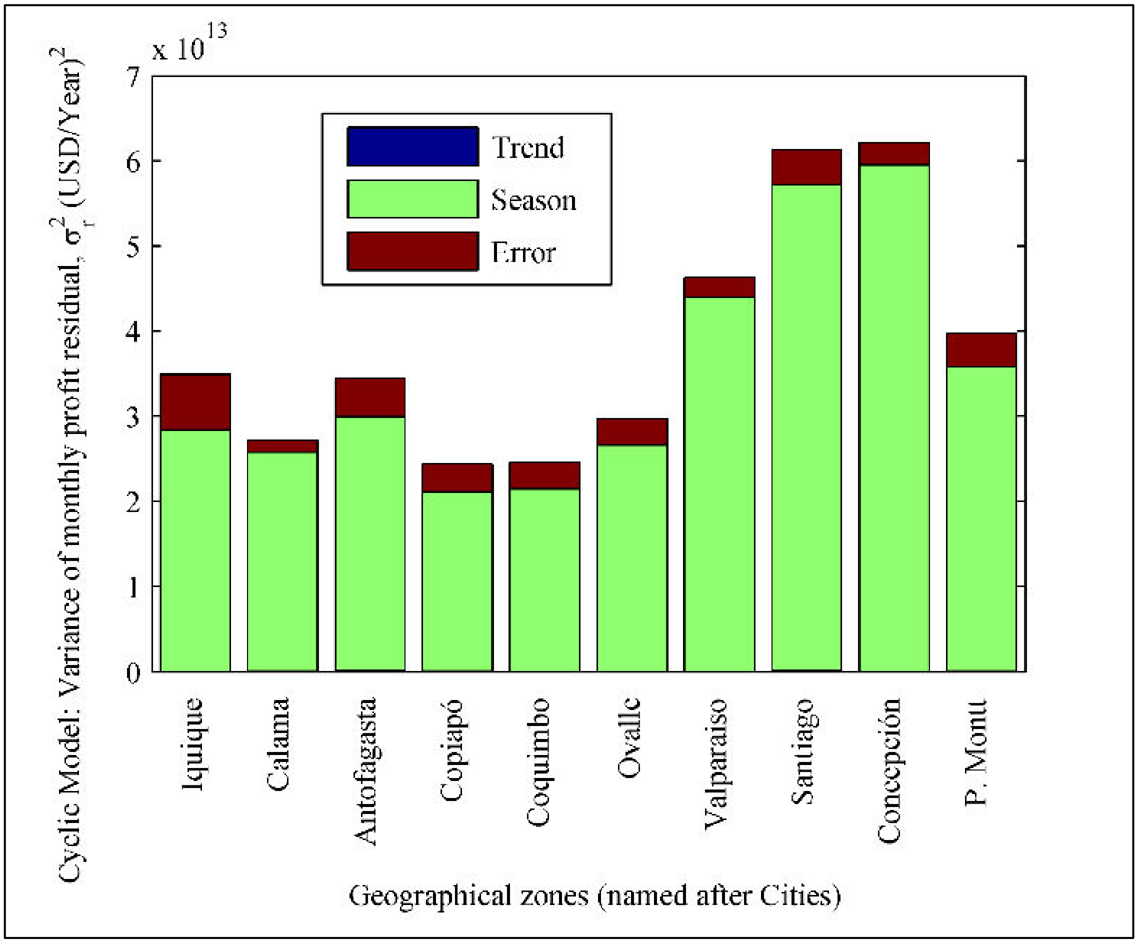


Figure 2-14: Variance decomposition of monthly profit (Cyclic Model).

Seasonality, trend and residue.

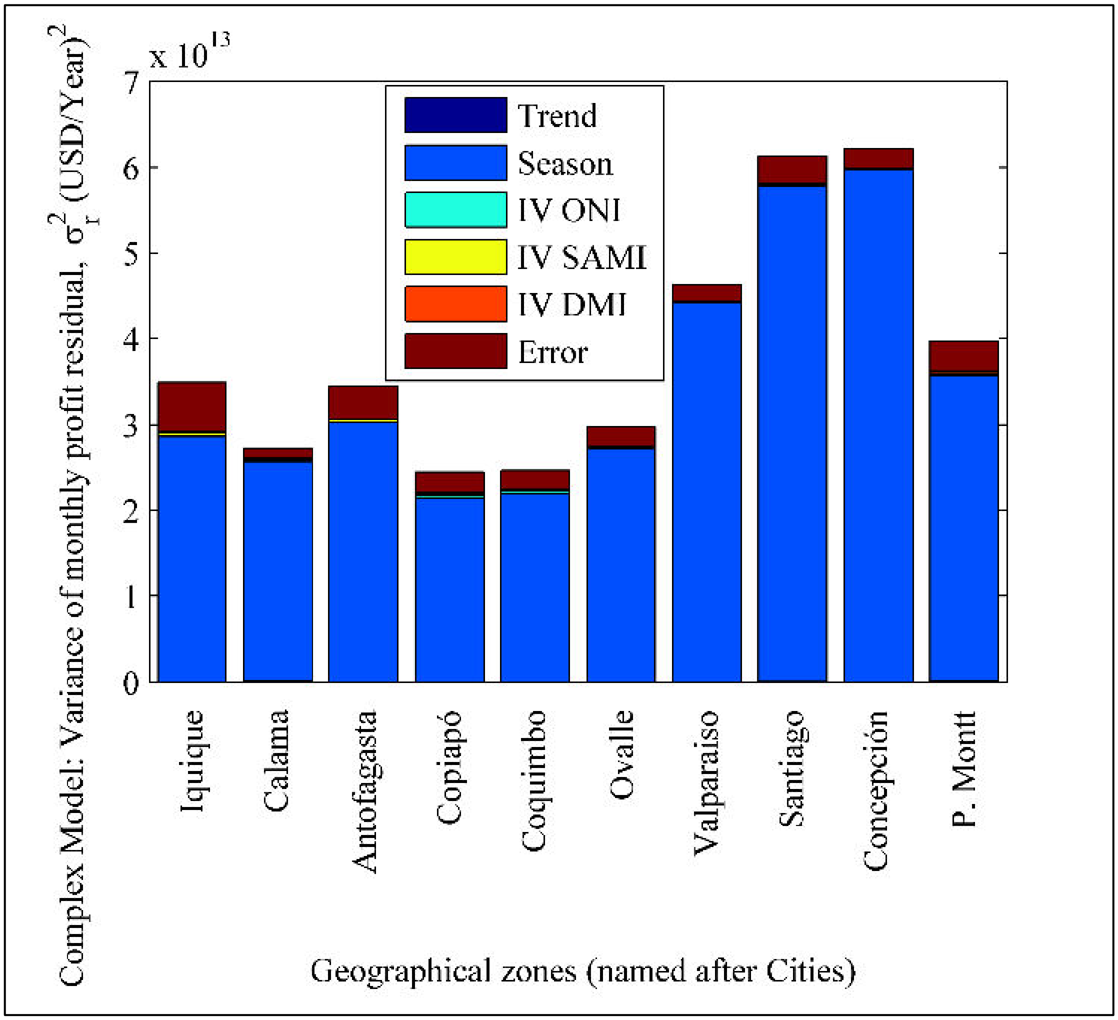


Figure 2-15: Variance decomposition of monthly profit (Complex Model).

Ocean-atmospheric oscillations, seasonality, trend and residue.

It is emphasized that the greatest reductions in risk of the Complex Model in comparison to the Cyclic Model occur due to oscillations in Copiapó and Coquimbo (Figure 2-12). In turn, the smaller reductions occur in the extreme regions (Iquique and Puerto Montt). This is because the ocean-atmospheric oscillations modulate the presence of the South Pacific Anticyclone heterogeneously across the Chilean coasts. The intensity of the anticyclone is modulated by El Niño Southern Oscillation (*ENSO*) and centers on winter (summer) of the Southern Hemisphere to the north of Copiapó (to the north of Conception) at latitude 25°S (36°S) as pointed out by (Ancapichún, 2012). A greater percentage of the variance explained due to the ocean-atmospheric oscillations between these cities is consistent with this approach.

For all the 10 Chilean cities presented, the coefficient of determination R^2 is greater for the Complex Model than for the Cyclic Model (Table 2-4). This result was expected since the residue (which represents the model error) is lower for the Complex Model. However, it is observed that this improvement in R^2 is sometimes marginal (ΔR^2 between 0.76% and 3.23%), considering that in the complex model 41 variables were used (in contrast to the 3 variables used in the cyclic model). This may pose a risk of overfitting that has not been analyzed in this work.

The expected profit for a photovoltaic plant of 100 *MW* in the 10 areas is of minimum -6.28 *MMUSD*/year and maximum 5.32 *MMUSD*/year (Table 2-4). The maximum profit was obtained for Calama and the minimum for Puerto Montt, being Calama and Santiago the only profitable locations. In the south, radiation and production is so low that at current PV investment costs the project makes losses. This comparison assumes the same selling price of energy in each of these areas.

The variability of radiation obtained from *NASA* is greater than that obtained from the Ministry of Energy of Chile between Iquique and Copiapó (Figure 2-6). Furthermore, the average radiation obtained from *NASA* is lower between Iquique and Ovalle (Figure 2-16) than the official one. This is because in the northern coast of Chile high cloudiness dissipates to the east within short distance. This increases the dispersion and reduces expected profit because of the coarse spatial resolution used (1ºlat./long. for *NASA*) that integrates both atmospheric conditions into the same zone.

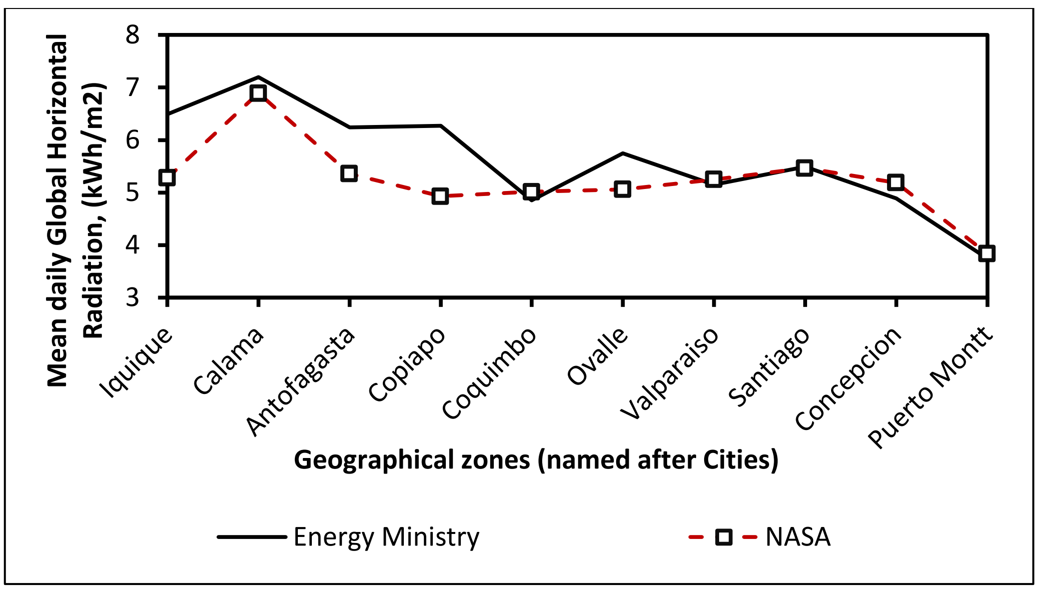


Figure 2-16: NASA and Chilean Energy Ministry databases differences. Lower values of average daily Global Horizontal Radiation for NASA are due to low spatial resolution integration of high coastal cloudiness with continent's clear skies in northern Chile.

All results were obtained based on the following assumptions: a) energy conversion efficiency is constant, b) energy tariff is 0.1 *USD/kWh* (because it is protected by a contract of sale of energy), c) costs (investment and operation) are constant and d) discount rate is $r = 10\%$. Additionally it was found that the model and the residue are uncorrelated ($Cov\ (m, r) = 0$) for all cities presented.

In summary, profit models used in this work (incorporating information on solar radiation and ocean-atmospheric oscillations) add value to investors reducing their risk through the new information provided. More specifically, an investor with basic information (cyclic seasonality) can substantially reduce his/her risk in relation to an investor who uses the methodology currently applied by financial institutions, lowering the variance of the profit at least 1/5 of the original. In addition, the information associated with the ocean-atmospheric oscillations can further reduce the risk to long-term consistently for all cities presented here (from 6% to 13% of the inter-annual variance). However, this last reduction is given at a high cost of additional complexity.

Table 2-4: Variance of models and methods: Standard methodology (Variance of GHI), Cyclic Model and Complex Model. Monthly profit (USD/day)^2

	Std. Method (Monthly Profit)			Cyclic Model				Complex Model						
Chilean Cities	**Mean**	**Std. Deviat.**	**Var.**	**R^2**	**Var. explain. by Trend**	**Var. explain. by Season**	**Var. of Residual**	**R^2**	**Var. explain. by Trend**	**Var. explain. by Season**	**Var. explain. by ONI**	**Var. explain.by SAMI**	**Var. explain. by DMI**	**Var. of Residual**
	kUSD/yr	kUSD/yr	(MM USD/yr)^2	(%)	(MM USD/yr)^2	(MM USD/yr)^2	(MM USD/yr)^2		(MM USD/yr)^2	(MM USD/yr)^2	(MM USD/yr)^2	(MM USD/yr)^2	(MM USD/yr)^2	(MM USD/yr)^2
Iquique	-1384	5916	34.85	81.3	0.029	28.32	6.515	83.8	-0.028	28.71	-0.078	0.341	0.302	5.663
Calama	5349	5223	27.13	94.7	0.090	25.64	1.436	95.5	0.105	25.54	0.048	0.073	0.176	1.218
Antofagasta	-818	5853	24.55	86.8	0.146	29.80	4.535	88.6	0.049	30.20	-0.081	0.331	0.023	3.921
Copiapó	-1794	4940	24.36	86.4	0.082	20.99	3.297	89.7	0.018	21.39	0.122	0.397	-0.131	2.515
Coquimbo	-1605	4940	24.55	87.2	0.004	21.39	3.148	90.3	0.004	21.98	0.248	0.182	-0.234	2.386
Ovalle	-1322	5444	29.70	89.4	-0.001	26.53	3.148	91.6	-0.002	27.13	0.184	0.159	-0.301	2.495
Valparaiso	-1322	6797	46.24	94.7	-0.001	43.76	2.445	95.5	-0.004	44.26	0.030	0.152	-0.248	2.069
Santiago	94	7835	61.19	93.2	0.104	56.93	4.158	94.4	0.056	57.62	0.214	0.167	-0.231	3.406
Concepción	-850	7866	61.98	95.7	0.010	59.40	2.653	96.5	-0.009	59.60	0.096	0.135	0.046	2.188
P. Montt	-6293	6293	39.70	90.2	0.091	35.74	3.871	91.4	0.122	35.35	0.231	0.089	0.517	3.406

2.10 Model extension and discussion

2.10.1 Extension of profit model incorporating subsidies and their impact on risk

Subsidies have been one of the key drivers of the international *PV* industry and have been applied in most of the world as transitional mechanisms to support their development, especially in the developed world. However, in the case of Chile, *PV* plants have been developed free of subsidies for several years, positioning this country as one of the first to reach competitive *PV* markets. It is for this reason that subsidies are not incorporated into the profit model developed above.

To extend the profit model to the rest of the world subsidies are incorporated. This is because in most countries *PV* industry has developed with this type of policy support.

To this end, the effect of 2 types of subsidies to the profit of the *PV* plant are analyzed: i) investment subsidies and ii) subsidies to the selling price of the injected energy.

In a competitive market profit margins are limited and due to downward variations in income (or upward variations in costs) profits of *PV* plants can be reduced. These variations could hinder the payment of their fixed costs potentially leading to bankruptcy or - if analyzed prior to investment – it could prevent getting bank-financing for the project (since banks only grant funding to projects with very low risk). Thus, the inclusion of subsidies improves profit of *PV* projects and reduces the potential risk of not generating sufficient revenues, generating losses or even falling into bankruptcy.

PV projects face a very low risk of increased cost beyond the initial budget, since most developers have signed a series of contracts (construction and purchases) before undertaking the project. Moreover, these projects typically buy insurances to cover small budget lines that may have an important impact on costs, such as unexpected changes in the exchange rate, accidents to persons or equipment, or any other unforeseen event. On the income side, banks only finance projects that have secured their income through long-term energy sale contracts (*PPA*), which is why projects usually have secured a purchase price. Very few merchant projects managed to be developed through self-funding, without an energy sales contract, or by selling on the spot market.

Given the cost and income structure of most *PV* projects, the largest source of variability is related to the present and future production, which may be affected by the following: i) climatological reasons or ii) loss of efficiency of different components.

Our work models and quantifies both effects, focusing on the variability of profit, which depends on the solar resource. As explained in detail below, this resource risk is not affected by the subsidy investment, which directly increases expected income from the *PV* plant. However, this risk is affected by subsidies to the energy injected into the system, because while subsidy increases, both expected profit and its variability increases.

The risk of bankruptcy - which is not the focus of this study - is reduced both by investment subsidies and by subsidies to the priced received by energy injected into the grid (Feed in Tariff - *FIT*), which facilitates the development and funding of this type of technology. The effects of both types of subsidies on the risk of bankruptcy are not the same, being the risk higher for subsidies to the injected energy than for those to the plant investment (when the expected increase of profits are equal) as explained below.

2.10.2 Profit models for *PV* plants in Chile

The monthly mean profit model $\bar{u}_m$ developed in subsection *2.3 Risk Structure and Profit Model* and expressed in (2.21) y (2.24) is an affine function, where the first term on the right side represents income (which depends on the monthly mean radiation $\overline{GHR}_m$) and the second term represents costs of investment and of *O&M*. In this model, radiation – and thus profit – are stochastic variables. Solar radiation $\overline{GHR}_m$ is partially predictable, which is used to predict profit $\bar{u}_m$ (2.26 - 2.28), decomposing

$\overline{GHR}_m$ into a part that corresponds to the model of radiation $m_{\overline{GHR}_m}(t)$ and a completely random residue $r_{\overline{GHR}_m}$. This is used to obtain a predictive model of profit and a residue that corresponds to the error between real profit and the model.

2.10.3 Risk due to production uncertainty in a *PV* plant

Because project developers hedge risks of *PV* projects in many ways, we consider that the risk is affected only by the variability of energy production. Due to the fact that variability of production is partially predictable - because it depends mostly on radiation - the part of the variability of profit that cannot be predicted is risk (strictly, we define risk as the standard deviation of the residue that is left after making the difference between the monthly mean profit and the modeled monthly profit).

Considering a linear model for the profit $m_{u_m}(t)$, which is based on a model that predicts solar radiation $m(t)_{\overline{GHR}_m}$, risk is as indicated in the following equations:

Model: $m_{u_m}(t) = K_m \cdot m(t)_{\overline{GHR}_m} - \bar{C}_m$ (2.46)

Risk: $\sigma_r = \sigma(\bar{u}_m - K_m \cdot m(t)_{\overline{GHR}_m})$ (2.47)

Next the addition of 2 types of subsidies are analyzed, i) lump sum, to support investment and ii) per unit of energy, to support the production and sale of energy.

2.10.4 Subsidy in *MMUSD*: Incorporation of investment subsidy to the profit model of a *PV* plant

A possible subsidy to a *PV* project would be a single payment at the beginning of its development to reduce the investment cost (lump sum). This subsidy *s* corresponds to an additional income, increasing the profit of the PV project, which is especially beneficial for investors given the high amount of investment required.

To extend the original profit model developed (2.26 - 2.28) with the investment subsidy s, a constant amount of money s simply must be added to the monthly mean profit $\bar{u}_m$, which improves the expected profit.

Monthly mean profit with subsidy in MMUSD:

$$\bar{u}_{m,s} = \bar{u}_m + s, \text{ where } \bar{u}_m = P_{E,t} R_{gain} A \bar{\eta}_{sys} \overline{GHR}_m - \left(\frac{AVI}{365} + \bar{C}_{O\&M,m}\right) \tag{2.48}$$

Profit variance including an investment subsidy does not change because s is constant as shown in the following equation.

Profit variance of the monthly mean with subsidy:

$$\sigma^2(\bar{u}_{m,s}) = \sigma^2(\bar{u}_m) + \sigma^2(s) \text{ where } \sigma^2(s) = 0 \tag{2.49}$$

Therefore, the profit simply moves rightward increasing its magnitude in the amount of subsidy s but does not change its variability. However, the investor will benefit and its bankruptcy will be less likely (Figure 2-17).

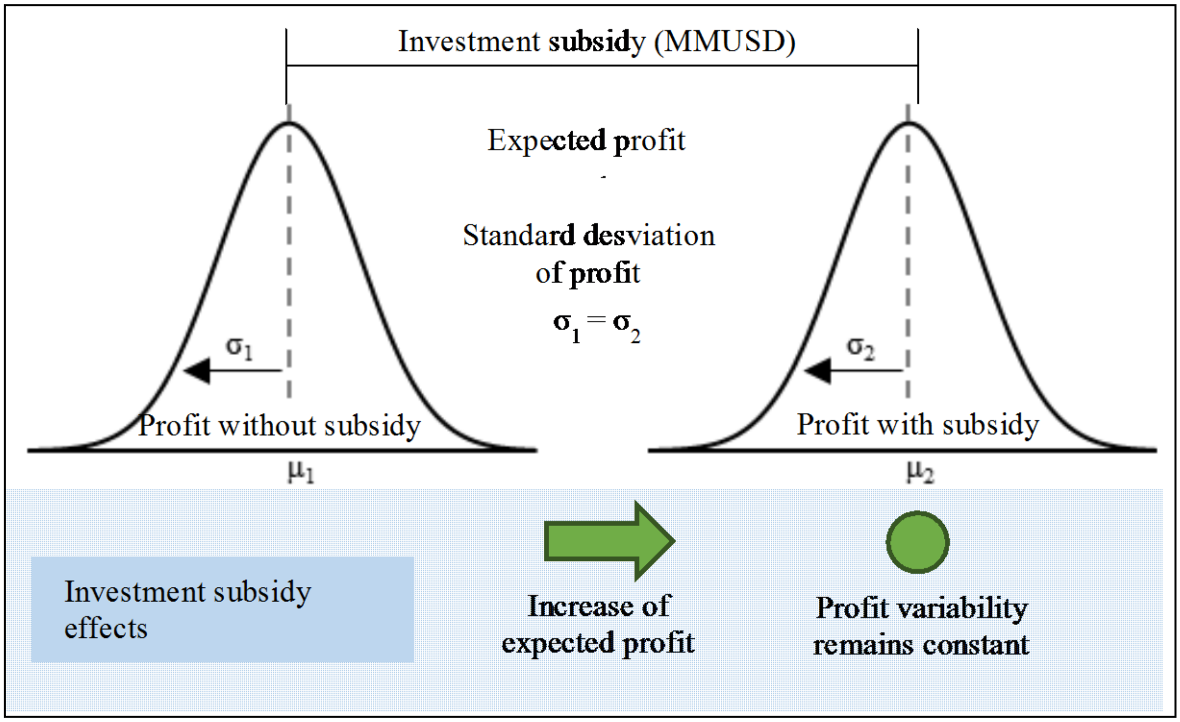


Figure 2-17: Investment subsidy increases income, maintains profit variability unchanged (constant) and reduces risk of bankruptcy.

2.10.5 Subsidy in *USD/MWh*: Incorporating subsidies to the price of injected energy (*FIT*) into the profit model of a *PV* plant

In many counties the electricity injected into the power system is subsidized with the so-called Feed In Tariff (*FIT*), a mechanism that often provides higher long-term rates than available in the competitive market, thus improving incomes of *PV* projects. Typically, investors subsidized by *FIT* receive a constant amount per unit of energy injected into the grid P_{FIT} that is higher than could be achieved by a negotiated contract between private parties in the electricity market, $P_{E,t}$ in profit model (2.26-

2.28). This increases the perceived income per unit of energy of the investor by an amount equal to $\Delta P = P_{FIT} - P_{E,t}$, often turning the economics of projects feasible.

To extend the original profit model developed (2.26 – 2.28) with the *FIT* subsidy, the energy selling price $P_{E,t}$ has to be replaced by the new subsidized tariff $P_{FIT} = \Delta P + P_{E,t}$, which improves expected profit proportionally to the increase of selling price perceived by the investor.

Monthly mean profit with subsidy in *USD/MWh*:

$$\bar{u}_{m,s} = (\Delta P + P_{E,t}) \cdot Q - C\ , \qquad \text{where}$$

$$Q = R_{gain} A \bar{\eta}_{sys} \overline{GHR}_m \text{ y } C = \frac{AVI}{365} + \bar{C}_{O\&M,m} \tag{2.50}$$

Profit variance including subsidy is the sum of the variance due to the subsidy FIT and the variance of the profit without subsidy as shown in the following equation. Here covariance is null because FIT rates are assumed constant.

Monthly mean profit variance with subsidy:

$$\sigma^2(\bar{u}_{m,s}) = \Delta P^2 \cdot \sigma^2(Q) + {P_{E,t}}^2 \cdot \sigma^2(Q) - \sigma^2(C), \qquad \text{where } \sigma(C) = 0$$

$$\sigma^2(\bar{u}_{m,s}) = \Delta P^2 \cdot \sigma^2(Q) + \sigma^2(\bar{u}_m) \geq \sigma^2(\bar{u}_m) \tag{2.51}$$

Unlike the investment subsidy, the risk associated with *FIT* (understood as residue variability not explained by the model) increases by increasing the selling price of energy. In other words, the standard deviation of profit increases in proportion to the increase in energy price $\sigma(\bar{u}_{m,s}) - \sigma(\bar{u}_{m\cdot}) = \Delta P \cdot \sigma(Q)$. Therefore, the expected profit of the investor and its standard deviation increases in proportion to the rise of the selling price perceived by the investor. Because the variation coefficient of solar radiation is always less than one (Figure 2-5), the increase of the expected profit will always be greater than the increase of the variability, which implies that the risk of bankruptcy will always be reduced in absolute terms (Figure 2-18).

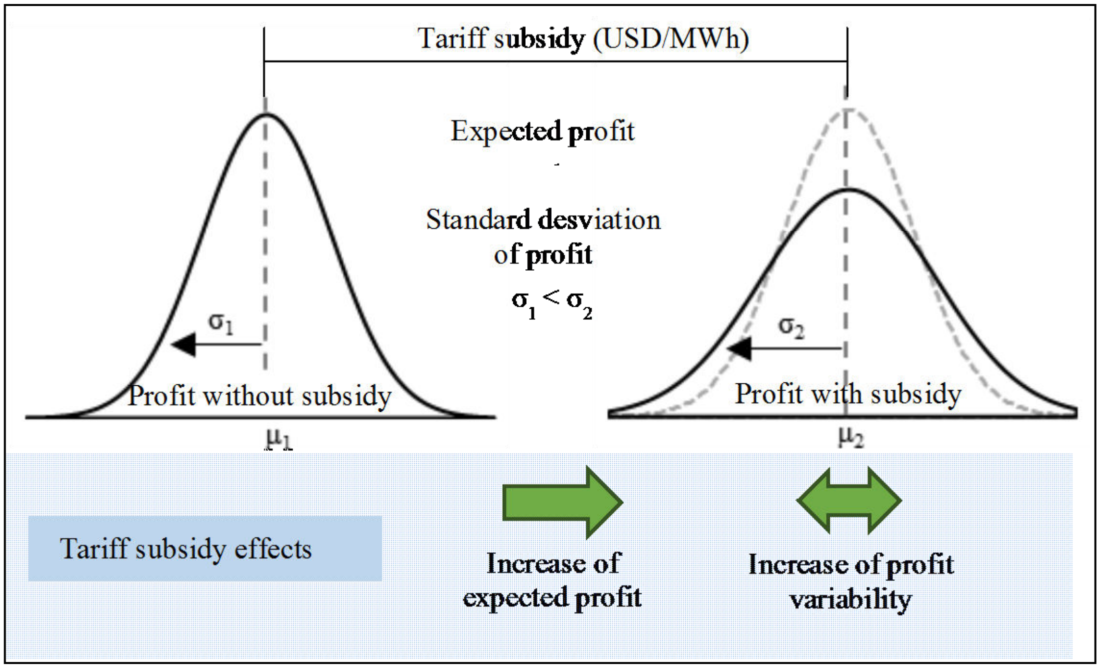


Figure 2-18: Subsidy to the injected energy into the grid (Feed In Tariff – *FIT*) increases income and profit variability in the same proportion and reduces risk of bankruptcy (because the variation coefficient of solar radiation is always less than 1 for all Chile).

2.10.6 Comparative analysis of bankruptcy risks for investment risks and Feed In Tariff

The investment subsidy and the subsidy *FIT* both reduce the risk of bankruptcy as explained in detail in the previous two subsections. However, given the same increase of the expected profit for both subsidies, *FIT* increases the variability of profit (while subsidies to the investment do not). This implies that *FIT* has a higher bankruptcy probability than lump-sum subsidies because its tail of profit's distribution is larger than the tail of investment subsidies (Fig. 2-20).

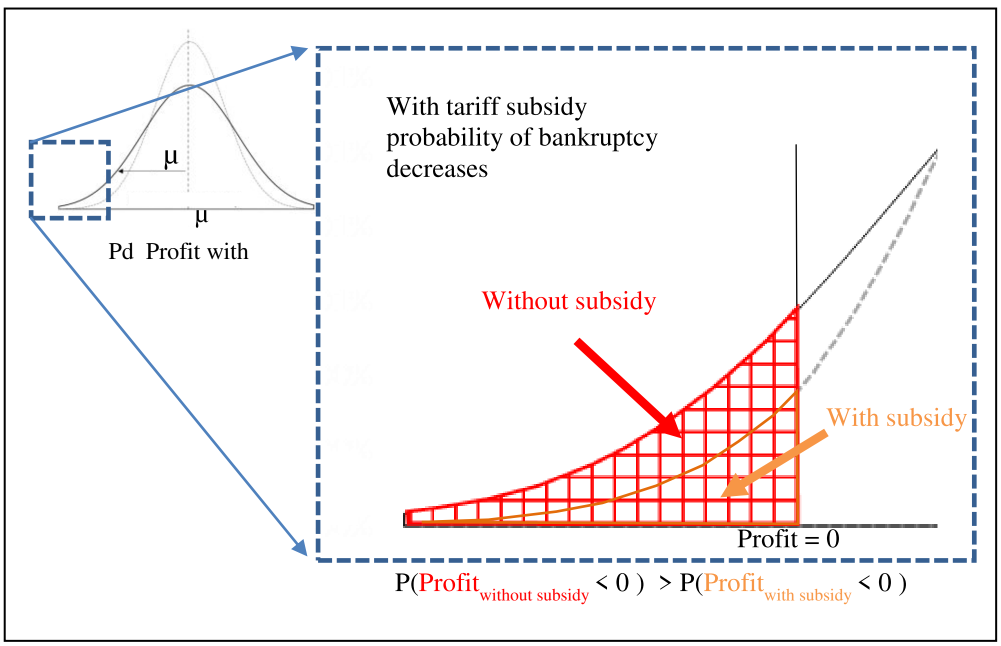


Figure 2-19: Subsidy to the energy injected to the grid (*FIT*) has a higher probability of bankruptcy than investment subsidies; give the same expected increase of profit for both.

2.10.7 Impact of the increase of *PV* generation in the Chilean electrical power system due to investment risk reduction

Incorporating the information contained in solar radiation and the ocean-atmospheric oscillations investors reduce their perceived risk in *PV* projects. This reduces discount rates they use to evaluate projects and/or lower the costs of financing them. In turn, this would shift more *PV* projects into the list of cost effective ones, increasing *PV* project deployment and *PV* production. In summary, by reducing the risk perceived by an investor, a greater *PV* deployment is expected. By extending our work to wind energy, hydroelectricity (which already uses *ENSO* to predict hydrology) and perhaps tidal power generation (with wave power) it is possible to think of a greater penetration of the renewable energy generation sources.

The increased penetration of renewable energy can be represented by the so-called duck curves over the daily net-load curve (demand to be supplied by conventional generation, or simply total demand minus wind and solar generation). Using more solar PV energy (as it is the focus of this study), these curves show the daily net-load profile with different penetrations of solar *PV*, which tend to depress net-load during hours when solar radiation is the highest. The following figure shows this effect in Chile, considering the current daily mean load profile and *PV* installed capacities of 500, 1000, 1500 and 3000 *MW* (Figure 2-19).[15]

[15] Simulations were performed using a proprietary model of the Pontificia Universidad Católica de Chile (PUC) and the estimated generation and demand scenarios were based on information of the Chilean electrical system of 2014.

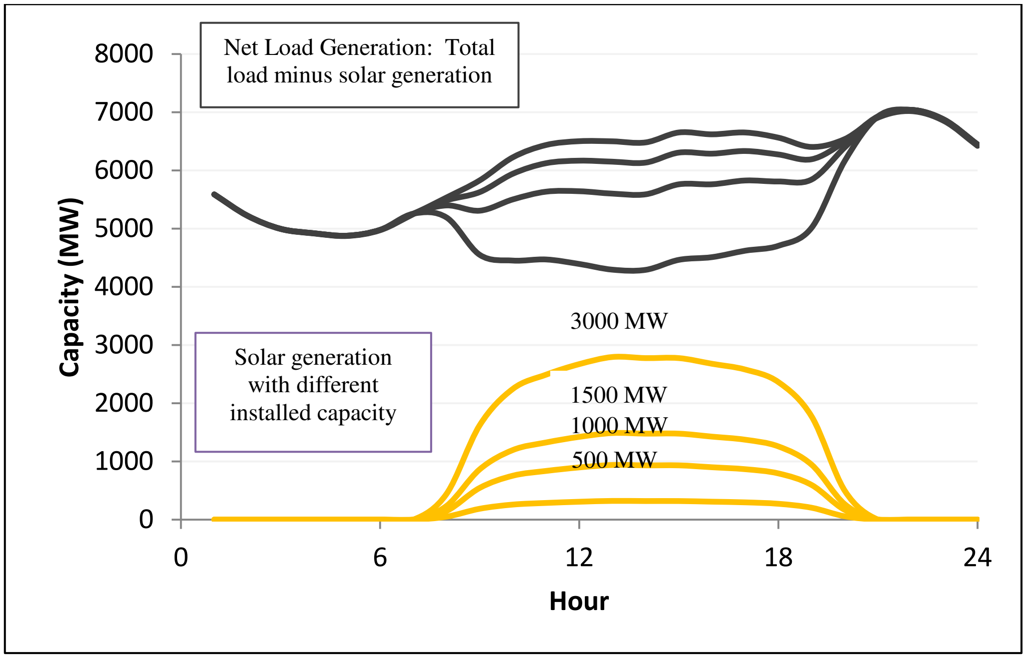


Figure 2-20: Impact of the increase of *PV* generation in the Chilean electrical power system (Duck Curve).

2.11 Conclusions

Despite impressive global development of solar photovoltaic energy over the last decade, the risk assessment of photovoltaic plants is not yet mature and has significant shortcomings. It is essential to recognize that the long-term profit variability is mainly explained by solar radiation, which has a highly predictable component that must be removed from the financial risk to make investment decisions.

An extensive review of literature presented in this study reveals that academic literature and industry's practice have completely missed the transcendental fact that financial risk perception of investors shall be reduced through predictable climate information. Even related topics reviewed show very few studies and significant voids, which are all identified. Significant literature exists explaining the relationship between solar energy and risk or for ocean-atmospheric oscillations. In contrast, no studies where found relating *PV* risk with climate predictability, developing profit models for *PV* risk assessments, relating Value Of Information with investment or oscillations among others. In addition, very few studies relate energy to ocean-atmospheric oscillations (none of them for the south-east Pacific coast) and most studies are exclusively technical and do not reach the economic, financial or commercial level. In regard to traditional risk assessment methodologies used in *PV* industry, the Typical Meteorological Year (*TMY*) is standard, which estimates risk directly from the variability of the return or of the present value of profit (essentially a simple calculation of means and variances).

This study conducts an extensive review, identifying relevant literature voids and making propositions that converge into an original methodology to calculate the reduction of the risk associated with the investment in a photovoltaic plant when the effect of solar resource predictability is properly accounted for. A new long-term profit risk model was specially proposed which captures the predictable climate information contained in both solar radiation and ocean-atmospheric oscillations. Exploiting this predictability, this study shows that in Chile the risk perception of market players is substantially reduced by up to 81%.

Northern Chile's high solar radiation and low variability, high electricity prices and falling technology costs have made of Chile the largest and fastest growing country in the deployment of solar projects for the *LATAM* region. Without any subsidies, the solar annual installed capacity has grown from 6 *MW* in 2013 to 536 *MW* in 2015 with a portfolio of thousands of *MWs* approved by the local environmental assessment system (*SEIA*). This paper presents the average radiation and the corrected productive risk of a typical photovoltaic plant in 10 areas across this country, being of interest to all decision makers involved in the electricity market as investors, regulators and financial institutions.

Risk reduction was calculated thanks to the information captured by 2 different profit models from solar radiation and ocean-atmospheric oscillations (with respect to the standard methodology - without model). The models are based on the Value of Information (*VOI*) Theory and were constructed with different information and complexity: a) Cyclic Model: characterized by intra-annual seasonality and trend of solar radiation; b) Complex Model: characterized by 3 ocean-atmospheric oscillations that affect climate in Chile (El Niño Southern Oscillation *ENSO*, Southern Annular Mode *SAM*, Indian Ocean Dipole *IOD*), besides solar radiation's seasonality and trend.

Risk reduction through climate modeling affects investment portfolios in power generation. By eliminating predictable climate variability of individual photovoltaic projects, risk perception decreases. These projects must be incorporated into portfolios through the application of Modern Portfolio Theory (*MPT*). Risk reduction achieved will have an impact on the efficient frontier of portfolios (depending on whether these projects are laying on it). Future work could quantify this effect including also other energy sources such as wind energy.

Results show that climate models are critical for investment in photovoltaic projects as they present dramatic reductions in risk from 60% to 81% for the 10 selected areas of Chile with respect to the standard methodology. This contributes decisively to improve the bankability of photovoltaic projects. A typical solar project of 100 *MW* in these areas reduces its risk from 4.93 - 7.88 *MMUSD*/year (traditional model) to 1.11 - 2.38 *MMUSD*/year respectively (proposed model). Under standard methodology (base case) risks are low to the north of Valparaiso. Southward of this city risks increase, reaching its maximum in Concepción and decreasing again towards Puerto Montt (due to permanently covered skies). The lowest risk is presented in Copiapó (North-central Chile) due to low cloudiness.

For Chile, the largest risk reduction is explained by the intra-annual seasonality of solar radiation (81% to 96% of the variance of profit in the 10 zones) which already represents a significant improvement over the standard methodology used. Seasonality reduces the risk with greater emphasis on the south of Chile and declines its influence northward. The most significant influence occurs in Concepción (South-central Chile) and the least in Iquique (northern Chile). Even more, ocean-atmospheric oscillations decrease the risk between 6% and 13% with a maximum influence in Copiapó, decreasing both to the north and south of this city. It is precisely in Copiapó where the vast majority of projects are being deployed in the country, facing a greater exposure to the ocean-atmospheric oscillations.

To determine the influence of the ocean-atmospheric oscillations, models were adjusted to characterize a spatial and temporal relationship between the oscillations and the solar radiation in a non-linear form. As a first step, a model was adjusted to the dynamic changes of each ocean-atmospheric oscillation (affected by climate phenomenon such as Rossby and Kelvin Waves). Then, these models were recalibrated for 10 geographical areas in Chile, considering that each oscillation has a different impact on dissimilar locations.

Furthermore, risk reduction has a structure with diminishing returns regarding the amount of information and complexity of the models. Thus, the risk relative to the standard methodology decreased due to seasonality and trend from 57% to 79% using only 3 variables for this model at all 10 locations. If ocean-atmospheric oscillations are added (on top of seasonality and trend), risk is further reduced from 6% to 13%, but this requires 38 additional variables, increasing complexity substantially.

Note that for an investor protected by contracts inter-annual variations are crucial as these will define the information asymmetries between investors. This occurs because an improvement of the climate knowledge frontier will be due to a better predictability of ocean-atmospheric oscillations in contrast to the intra-annual seasonality, since the former present a greater challenge. For inter-annual variabilities there is very little knowledge, predictability is low and complexity very high (38 variables). In contrast, for seasonality and trend there is a large literature body, predictability is high and complexity is low (3 variables).

Climate models with different predictive capabilities involve investors with different risk perceptions, causing information asymmetries. These differences may be important enough to make a project profitable (bankable) for one investor but for another. In more industrial terms, the insured profit (or P95 profit) required to finance a project will be higher when it has been backed up by a more accurate model (considering constant expected profit). For example, an investor that is capable of predicting ocean-atmospheric oscillations perceives a risk between 6% and 13% lower than a competitor who can only predict solar radiation's seasonality and long-term trend in Chile. At the margin, some projects will be profitable for this investor and not profitable for his/her competition.

Furthermore, good modeling can reduce the risk perception of financial institutions. This would reduce costs for both the investor and the financier and improve the bankability of PV projects. The former would receive lower interest rates and the latter should provision fewer risks. Similarly, the investor's costs by hedging the variability in solar resource would also be lower.

Asymmetries between investors also impact the competitiveness of markets, which highlights the criticality of climate models. Investing in a good model can represent a competitive advantage because it reduces the risk of solar generation projects and improves the efficient frontier of technological mix. In the long term these imbalances are unsustainable and the use of models would become a standard in the industry.

In the short and medium term, and from the point of view of maximizing the social benefit, the individual efforts of each investor could be pooled in a public climate model of the highest quality, instead of leaving the development of these models to each of the market players. This would allow the creation of a greater fund that in turn would allow investment in a more sophisticated model to do the best possible predictions. Thus, the risk of all generators would be minimized, information asymmetries would be eliminated and industry competition would deepen.

Beyond *PV* cost reduction, different initiatives that support *PV* generation could increase its penetration and investment further. Subsidies and massive risk reduction due to climate predictability are examples of those initiatives. Therefore, for the Chilean power system, different *PV* penetration scenarios are analyzed (500, 1000, 1500 and 3000 *MW*), assessing the depression of the daily net-load profile during hours of higher solar radiation (Duck Curve).

The most important initiative to support PV around the world is the use of subsidies. Thus, the profit model proposed is extended to be used in countries where subsidies are relevant *PV* market drivers (almost all developed counties). The effects on expected profit, profit variability and bankruptcy risk is analyzed for 2 types of *PV* subsidies or supporting policy: i) subsidies to the investment and ii) subsidies to the energy injected into the grid (Feed in Tariff – *FIT*). Both subsidies improve the expected profit of the investor but, investment related subsidies are more effective against bankruptcy risks, since they maintain profit variability unchanged (compared to subsidies to the energy injected which increase variability), although both reduce bankruptcy probability.

3 NOVEL METHODOLOGY FOR MICROGRIDS IN ISOLATED COMMUNITIES: ELECTRICITY COST-COVERAGE TRADE-OFF WITH 3-STAGE TECHNOLOGY MIX, DISPATCH & CONFIGURATION OPTIMIZATIONS

3.1 Introduction: Access to electricity is critical worldwide and microgrids are a potential solution

Access to electricity is critical worldwide because it is a barrier that ones overcome may reduce poverty, enhance access to health-care and education, and boost economy, thus reducing poverty and improving quality of life (Buchholz & Da Silva, 2010; Deichmann et al., 2011). Nevertheless, 1.1 billion people (around 17% of world's population) have no access to this energy source (*Global Tracking Framework*, 2015, *World Energy Outlook 2015. Chapter 2: Energy Access*, 2015). Despite efforts made to extend the central distribution grid in recent years (Schnitzer et al., 2014), a large number of rural, remote and scattered communities are still without access to electricity due to the high expansion cost(Bhandari, 2011; *Global Tracking Framework*, 2015). Microgrids are probably one of the most feasible alternatives in these cases.

3.1.1 Access to electricity in *LATAM* impacts 25 million people in rural areas.

Over twenty millon people have no access to electricity in Latin America and the Caribbean (*LAC*) despite of large effords made in past decades to expand de distribution systems through specific government programs. This is a very poor electricity coverage when compared to the developed world standard (*Global Tracking Framework*, 2015). Nevertheless, as has happen in other continents, low population densities (Yadoo & Cruickshank, 2010) or geographic remoteness (e.g., the Amazon and Andes regions) have seen limited success, even when government programs have included subsidies to stand-alone systems with specific technologies (Montecinos & Watts, 2015).

3.1.2 Electrification programs have often provided electricity at high prices (e.g., diesel) while failing to recognize that higher prices imply less consumption.

The lack of success of electrification programs in rural remote areas can often be explained by their failure to recognize at least three dimensions of the problem: i) The different values a community assigns to distinct energy services, ii) the organizational and social challenge around an isolated microgrid and iii) the estimation of the potential community's electricity demand.

The potential demand (iii) of an isolated microgrid is very hard to estimate both due to the inexistence of historical consumption patterns in communities without electricity access (Schnitzer et al., 2014), as well as limited availability of studies on socioeconomic and cultural drivers of electricity demand (although some attempts have been made using neural networks (Llanos, Saez, Palma-Behnke, Nunez, & Jimenez-Estevez, 2012). The organizational and social challenge (ii) is relatively new for power systems and can represent a barrier as well as an opportunity due to the increasing involvement of communities (Agostini, Nasirov, & Silva, 2016; Komendantova & Battaglini, 2016). Some authors have explored this challenge for small-scale remote microgrids and other electrification alternatives, showing that solutions are successful for specific cultural contexts. This means effective experiences in some places are not always transferable to others. Schnitzer (Schnitzer et al., 2014) identifies some critical social and organizational factors which enable a microgrid to enter a virtuose (successful) or vicious (unsuccessful) cycle, such as strategic planning, operational design and social context. Yadoo (Yadoo & Cruickshank, 2010) compares dealership approaches, concessionary models and strengthening of small to medium energy businesses and argues in favor of cooperative business. Montecinos proposes a self-managed electrification for isolated indigenous communities in Chile (Montecinos & Watts, 2015) and Saez (Sáez, 2015) a specific participatory model for the Mapuche's culture, indigenous inhabitants of southern South America. Most authors point to community involvement, community leaders' engagement, local maintenance, self-protecting design, and partial community financing as key drivers for success.

Communities assign different values to distinct uses (i) of energy. Electrification programs have failed to recognize this critical fact, especially outside areas under supply obligation by public utilities. Outside these areas, when a community has reached electricity prices around 40 *USD/MWh*, it's implied that it will satisfy almost all its needs, including high levels of sophistication. Conversely, when electricity is supplied at much higher costs (200 to 300 *USD/MWh*) in limited income areas, only a small amount of the potential needs of the community are satisfied, forcing them to prioritize, e.g., lighting a few hours a day, refrigeration of critical food, *TV*, etc. Electrification programs have failed to recognize this reality, sometimes providing electricity at very high costs, greatly depriving the community from the use and benefits of this electricity. The supply has usually been diesel at very high costs so communities often reduce their use to only a couple of hours a day.

3.1.3 Microgrids can improve electrification by reducing costs and enhancing electricity coverage by considering local reality.

Electrification programs in *LATAM* have also neglected the fact that nowadays an optimal combination of renewable and conventional generation (together with energy storage systems) may reduce costs and increase electricity coverage substantially if local costs are taken into account (e.g., renewable energy costs due to local energy potential, and fuel & technology costs due to the isolation of a community). These optimal - tailor made - hybrid systems are possible today with the use of microgrids (C Bustos, Watts, & Ren, 2012; Lasseter, 2002; Lasseter & Paigi, 2004; Ma, Yang, Lu, & Peng, 2015; Mazzola, Astolfi, & Macchi, 2016): small electricity grids (usually under a few *kW*) that can be isolated or connected to the distribution system and have microgeneration as well as auto-consumption). Thus, microgrids may benefit a large number of communities by improving today's electrification programs in *LATAM*, correcting their tendency to select some technologies a priori (e.g., diesel and *PV*) and discarding others (e.g., gas and batteries). So far only Colombia has explicitly recognized the potential of microgrids in South America, where they are seen as a feasible solution (T. González & Cadena, 2015).

3.1.4 Example of the potential benefits of a microgrid in isolated communities of Chile

If the different values between distinct uses of energy are recognized and all technologies are optimally combined, a microgrid based tailor-made solution can be found for each community. For example, rural communities in the north-central regions of Chile that sell fresh butchered goats next to the highway would benefit from a microgrid. These communities lack refrigeration, which affects the quality and price of their products due to high local temperatures and intense radiation. The non-sold animals degrade to unhealthy conditions in as little as a few hours, discouraging potential buyers from purchasing them. This community - if electrified - would have a high valuation for the electricity for refrigeration and would have a low cost solar generation, thus being able to offer a high quality product that would be appreciated more by customers at a relatively low electricity cost (due to the advantage of local energy resources).

The remainder of this study is organized as follows: Section 2 proposes a novel methodology to construct a truly optimal cost-coverage trade-off for microgrids in isolated communities. Section 3 describes the main local characteristics of the case studied. Section 4 presents the Distributed Energy Resources (*DER*s) used in this study. Section 5 describes the robust dispatch optimization method used. Section 6 discusses the *DC* and *AC* configurations considered. Section 7 develops a model for the capacity optimization trade-off. Section 8 presents the trade-off curves obtained, the types of microgrids found and their cost structure. Finally, section 9 offers a conclusion to this study.

3.2 Novel methodology to construct an electricity cost vs. coverage trade-off in isolated communities' microgrids and the need to endogenize the Value of Lost Load.

Microgrids may represent the most reliable and cost effective solution to give access to electricity in many isolated regions in the developing world. As illustrated by Schnitzer (Schnitzer et al., 2014), in isolated communities, where only primitive energy exists (e.g., batteries, kerosene lamps, solar lamps or solar home systems), in the long-term only the most basic electricity services are covered and at a very high cost. These services include, for example, cell phone charging or essential lighting. With a microgrid, a community could reduce its cost per unit of energy, increase its consumer surplus and advance to more sophisticated (less critical) energy consumptions such as television, refrigerators and even productive activities (e.g., commercial activities or irrigation pumps) as shown in Figure 3-1 in the horizontal axis. One step further would be to include electrical demand response (*DR*) and heat demand to the operation of an isolated microgrid through Combined Heat and Power (*CHP*) systems. *DR* (Montuori, Alcázar-Ortega, Álvarez-Bel, & Domijan, 2014; Palma-Behnke, Benavides, Aranda, Llanos, & Saez, 2011) and *CHP* (Awad, Wu, Ekanayake, & Jenkins, 2011) have been studied, but without acknowledging the different values of distinct energy services and without providing social context.

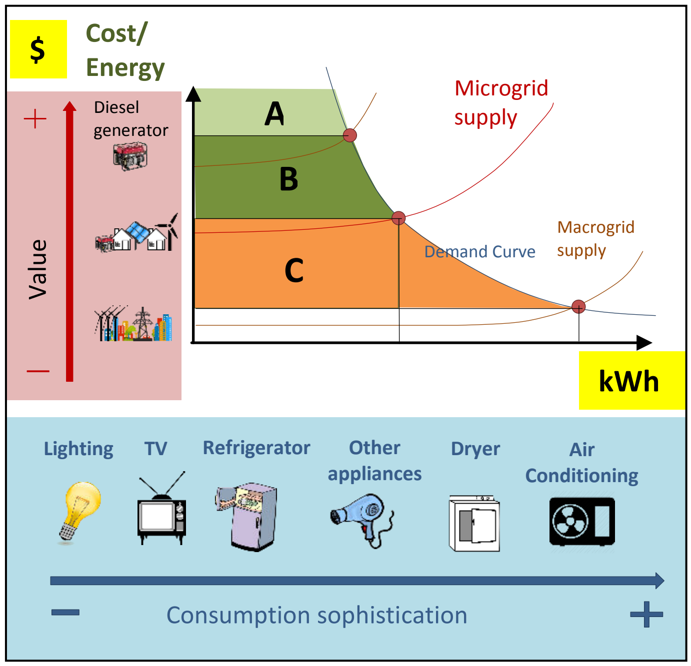


Figure 3-1: Long term Demand and supply equilibria of a community using a standalone diesel generator, a microgrid or a Macrogrid. The surplus for the consumer is represented by the area *A* for the diesel generator, by *A*+*B* for the microgrid and by *A*+*B*+*C*+*D* for the Macrogrid. The demand curve shows that the consumer values basic consumptions the most (e.g., lighting, *TV* and refrigeration). With increasing consumption sophistication, the consumer values an additional unit of energy less. Standalone diesel generators are expensive solutions and thus only satisfy more basic/valuable needs. The Macrogrid is the least expensive solution and supplies almost all consumptions. The microgrid is an intermediate solution allowing some degree of consumptions sophistication at a reasonable cost (self-elaborated

based on (Schnitzer et al., 2014) and (*Estudio de usos finales y curva de oferta de la conservación de la energía en el sector residencial*, 2010)).

Traditionally, supplying energy to the community through a Macrogrid can be thought as the lowest cost alternative, leaving the microgrid as an intermediate solution between the Macrogrid and a home system. However, under current cost and available technology, microgrids can be even less expensive than Macrogrids in some cases. This can be the case in some isolated regions where either the community is too far away from the Macrogrid, the communities are very distant from each other but each has a densely clustered population, or where plenty of energy resources are available. In all these cases, the cost to expand the traditional distribution system may be too high.

3.2.1 Communities' consumption depends on its $VOLL$, ENS_{mM} and $LCOE$

Consumers in isolated regions of developing countries may prioritize lower cost over complete coverage of their electricity needs while facing the electricity cost-coverage trade-off in their energy supply. This is due to their budget constraints and financial limitations, which force them to prioritize their basic needs.

The electricity coverage is based on the cost of supply and the willingness-to-pay of the community itself and it is a measurement of how far away the real consumption is from an ideal one with low cost supply (e.g., when real consumption is the same as the ideal one the coverage is 100%).

In this study, we consider two separate effects that can reduce the electricity coverage in the long term: i) consumption left out intentionally and ii) lack of reliable supply. These effects are detailed as follows:

a) Consumptions left out intentionally

Communities can prioritize electricity consumption to supply only their basic needs according to their budgets. This means they will not invest in appliances beyond their reach, where they cannot afford their energy consumption and appliance investment cost. In addition, they will use their own appliances only if they can afford to, i.e. their use is again limited due to their economic and financial restrictions.

Thus, if a microgrid has to be well-sized to supply such a constrained community, a decision must be made beforehand, at the conceptual design stage, to decide which services are going to be supplied and which ones should be intentionally left out.

Economically, the long-term cost of supplying these less critical services or consumptions should be higher than the Value Of Lost Load $VOLL$ of the community (which represents the cost per unit of energy not supplied to the load). In addition, the long-term mean energy price measured in this study in terms of the Levelized Cost of Energy, $LCOE$ (3.1) should be constrained by its budget.

b) Lack of reliable supply

An unreliable supply reduces the average energy consumed by the community, due to the eventual use of a more expensive technology giving reserve services or due to the obligation to leave loads unserved. In the long term, this reduces the mean energy consumption and raises supply costs (reducing consumer surplus).

In this study of cost coverage trade-off ($LCOE$ vs. ENS), we define the Energy Not Supplied of a microgrid m relative to an ideal Macrogrid M as ENS_{mM} (p.u.) as shown in Figure 3-2 and the electricity coverage as $1 - ENS_{mM}$ (during this study we will use ENS_{mM} or ENS interchangeably). Thus, the equations that describe $LCOE$ and ENS_{mM} are as follows:

$$LCOE = \frac{\sum_{t=1}^{n} \frac{I_t + O\&M_t + F_t}{(1+r)^t}}{\sum_{t=1}^{n} \frac{E_t}{(1+r)^t}} \tag{3.1}$$

$$ENS_{mM} = \frac{\sum_{t=1}^{n} P_{F,t}}{\sum_{t=1}^{n} P_{LOAD_t}} \tag{3.2}$$

where I_t is the investment in period t, $O\&M_t$ is the cost of $O\&M$ in period t, F_t is the fuel cost in period t, E_t is the generation of electricity in period t, r is the discount rate, n is the lifetime of the system, $P_{F,t}$ is the mean power failed to be supplied in period t relative to the level of consumption in the reference Macrogrid M, and P_{LOAD_t} is the mean power of the total load in period t that a community would consume if connected to that Macrogrid.

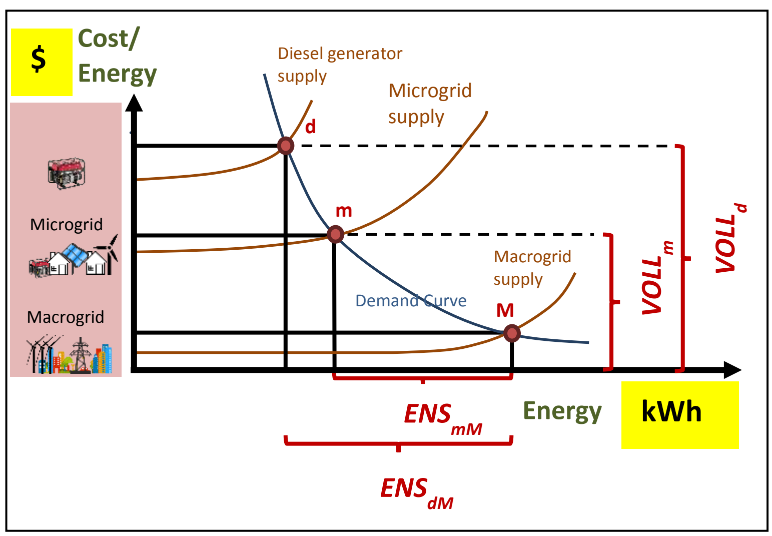


Figure 3-2: Isolated community's decision of the size of its electrical power system (i.e. microgrid or a diesel generator). The community has to decide how much Energy Not Supplied (*ENS*) is tolerable in comparison to a hypothetical Macrogrid (ENS_{dM} for the diesel generator and ENS_{mM} for the microgrid). The Value Of Lost Load ($VOLL_m$ for the microgrid and $VOLL_d$ for the diesel generator) limits the cost of the electrical system, i.e. microgrid's marginal cost of supply will always be less or equal

to *VOLL*. The selection of *ENS* and *VOLL* is a non-trivial decision because it depends of the particular demand and supply curve of the community, which normally are not well known (especially the demand curve). This decision determines the electricity coverage in relation to the Macrogrid and the final electricity bill.

3.2.2 Communities will naturally choose electricity cost and coverage combinations of a trade-off according to their needs

Ideally, a community - if faced with all possible microgrid designs and investment costs - would naturally choose a combination of *LCOE*, *ENS* and *VOLL* that best fits its needs. Wealthy communities in isolated areas self-supply electricity with high cost and very high coverage of their consumption. Since their budget is big and their *VOLL* is very high, their microgrids will supply electricity with very low *ENS*, often using a renewable and fossil fuel mix.

3.2.3 Traditional Method: Assume fixed *VOLL* and deliver only one optimal point (no trade-off to adapt to the community's needs).

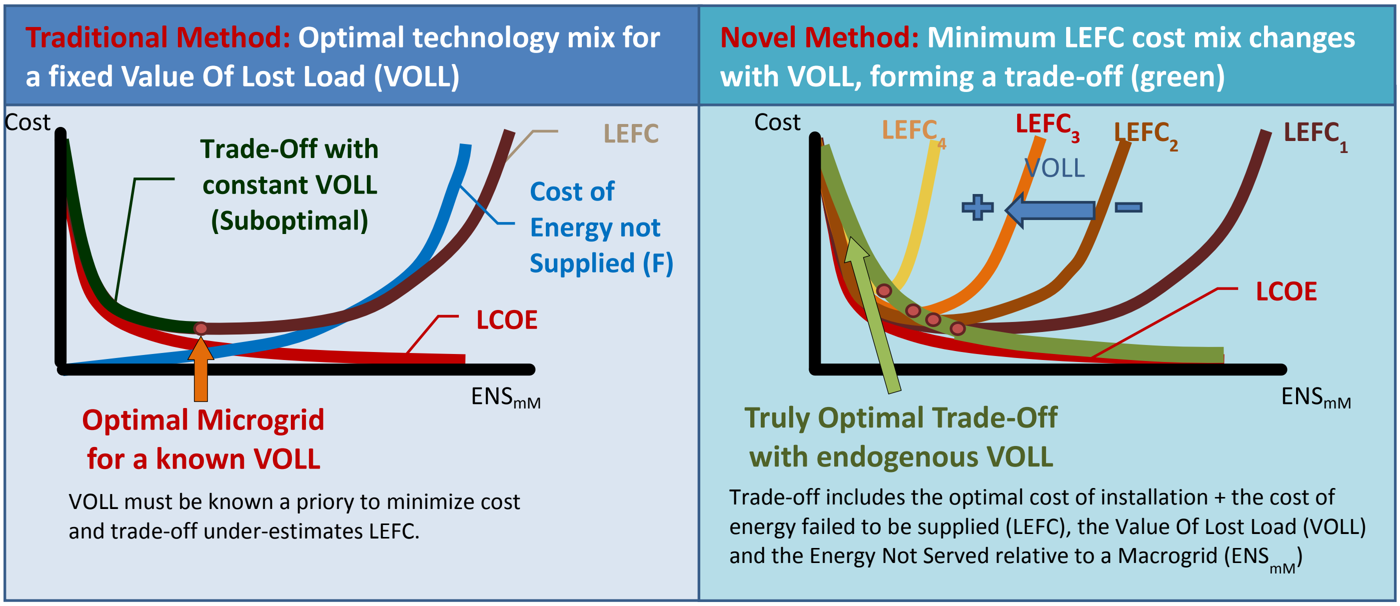
Traditional methods used to design electric grids are mainly targeted at the developed world and fail to consider a cost versus coverage trade-off that can adapt the supply system and its costs for the particular needs of an isolated community. Instead, they deliver an optimal demand-supply (or cost-coverage) equilibrium assuming *VOLL* is known and fixed, with *VOLL* much higher than average supply cost. These methods are based on the minimization of the *LCOE* (3.1) plus the cost of energy failed to be supplied F (3.3), the sum that in this study will be called $LEFC$ (3.4) as shown in Figure 3-3a.

$$F = VOLL \cdot ENS_{mM} \tag{3.3}$$

$$LEFC = LCOE + F \tag{3.4}$$

Normally $LCOE$ decreases with more ENS_{mM} because less critical (and thus more sophisticated) consumptions require higher long-term supply costs. On the contrary, with increasing ENS_{mM} the total cost of energy failed to be supplied (F) increases. In general a minimum can be found for $LEFC$ that represents the optimal total cost of the microgrid as can be seen in Figure 3-3a (Billinton & Allan, 2013) (although $LEFC$ is the best decision index to size the grid because it contains all the cost information, $LCOE$ represents the actual monetary costs that the community will have to pay).

3.2.4 Studies of electricity cost versus coverage trade-offs are unavailable. Cost-reliability trade-offs exist but are scarce and underestimate cost because they do not endogenize *VOLL*.



a) b)

Figure 3-3: Traditional and Novel Method to design a microgrid in an isolated community: a) traditional cost optimization method with fixed Value Of Lost Load (*VOLL*); b) Novel optimization method with electricity cost versus coverage trade-off and with endogenous *VOLL*. It is critical to have endogenous *VOLL* in order to avoid suboptimal cost estimation, as would be the case using the trade-off in the traditional method.

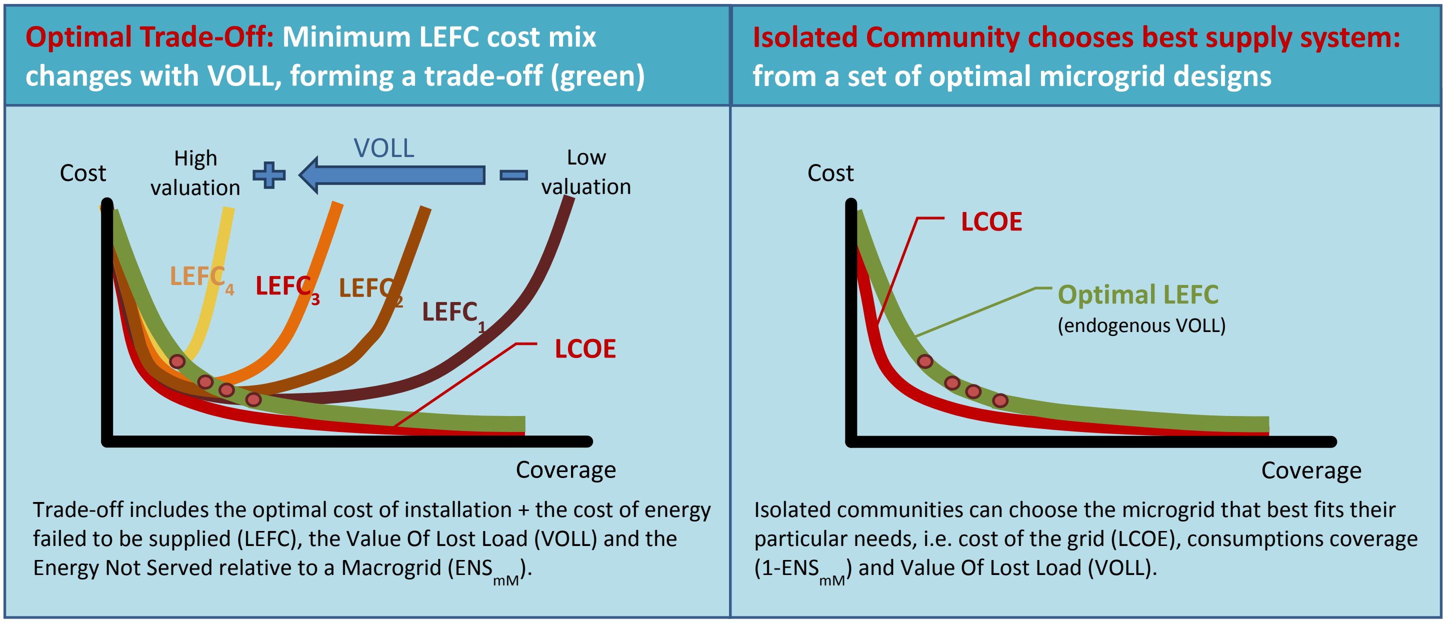
Pareto efficient trade-offs applied to microgrid's have been researched mostly in the last 5 years. This trade-off literature can be divided broadly in grid-tied and off-grid microgrid applications. For grid-tied microgrids in distribution systems, trade-offs have been used for solving the sizing and location problem of DER penetration (Buayai, Ongsakul, & Mithulananthan, 2012; Celli, Ghiani, Mocci, & Pilo, 2003).

For *CHP*/*CCHP* systems (Basu, Chowdhury, & Chowdhury, 2010; Kavvadias & Maroulis, 2010) costs, emissions, reliability, and production have been used as objective functions.

Studies on trade-offs in isolated microgrids with multi-objective optimization are scarce and mainly focus on supply cost vs. emissions (F A Mohamed & Koivo, 2008; Faisal A. Mohamed & Koivo, 2012; Sachs & Sawodny, 2016) or cost vs. reliability (C Bustos et al., 2012; Lee, Soto, & Modi, 2014; *Residential Off-Grid Solar + Storage Systems: A Case Study Comparison of On-Grid and Off-Grid Power for Residential Consumers*, 2016). Some more sophisticated studies can be found with three to four objective functions (Abbes, Martinez, & Champenois, 2014; Perera, Attalage, Perera, & Dassanayake, 2013; Wu, Zhuang, Zhang, & Ding, 2016). All these studies center their attention mainly on the technological dimension of the problem, mostly proposing heuristics or methods to solve the optimization problems. Interesting is the article of Sachs, who designs a three stage optimization model similar to the one developed in our work, including capacity mix sizing, optimal dispatch and power electronics configurations, determining representative profiles through clustering (Sachs & Sawodny, 2016), however failing to include key economical and social dimensions into the discussion. On a more economical and practical ground the study of *EPRI* for residential off-grid systems concludes that in the *USA* distribution system tariffs are too low to allow disconnection from the grid. In this country off-grid systems would be 10 times more expensive than grid-tied systems at equal reliability level (*Residential Off-Grid Solar + Storage Systems: A*

Case Study Comparison of On-Grid and Off-Grid Power for Residential Consumers, 2016).

Explicit electricity cost-coverage trade-offs for isolated microgrids are nearly unavailable in literature today, besides the study of Lee, which includes at its sizing stage the need to define the percentage of electricity demand that a grid should deliver (Lee et al., 2014). Nevertheless, this study together with all available literature maintain the traditional approach of considering a constant *VOLL* for the trade-off. This is, failing to recognize that each community - if faced with all possible microgrid designs and investment costs - would naturally choose a combination of *LCOE*, *ENS* and *VOLL* that best fits its needs and that otherwise calculated trade-offs are suboptimal and tend to underestimate costs.



a) b)

Figure 3-4: Optimal electricity cost versus coverage trade-off helps isolated communities to choose their best electricity supply system (microgrid design), even when they do not know their particular needs in advance (demand and supply equilibria). It offers a set of optimally designed (size and technology mix) microgrids from which to choose, depending on the particular needs of the community, i.e. their electricity consumption coverage relative to a hypothetical Macrogrid (ENS_{mM}), their Value Of Lost Load (*VOLL*) and the cost the community is willing/capable to pay (*LCOE*).

The minimum cost microgrid design for the *LEFC* curve with fixed *VOLL* contains all costs, including the cost of energy failed to be supplied. This means that all other designs within this curve have a higher cost (are suboptimal). If a community wishes to have a higher electricity coverage, this is not rational with the same *VOLL* (because of the additional cost). It is only possible if *VOLL* has implicitly shifted to a higher value. This can be seen in Figure 3-3b.

A new, truly optimal trade-off curve was found, which contains all the minimum cost microgrid designs for each *VOLL*. Graphically, when *VOLL* increases, the convex *LEFC* curve tends to be squeezed to the left of the cost versus coverage graph, locating the optimal minimum cost design of each *LEFC* (depending on *VOLL)* on a curve that is less convex and that has higher costs than the original *LEFC* curves with fixed *VOLL* (Figure 3-4). Thus, the traditional method of using fixed *VOLL* is suboptimal and underestimates costs.

1.1. Discussion on economic aspects of the new methodology

The new methodology proposed focuses on cost estimation from a private investor's perspective because if costs are properly sized or estimated, they can be used to ensure revenue adequacy to μG developers who operate the grid wisely. Nevertheless, we do not focus much on how these costs could be shared among the community. In principle, alternative business models and tariff designs could be developed, which is another research challenge very badly tackled in microgrid literature (Schnitzer et al., 2014).

While the simplest way to fund energy supply through a uG is a flat tariff, computed adding all the costs (monthly amortization of the investments, monthly operational, etc.) divided by monthly energy supply, this pricing alternative is inefficient, not flexible, and does not recognize resource availability and consumption patterns impacts on the grid. Alternative and more efficient tariffs schemes are a "connection fee" to fund the infrastructure investment (generation technologies, storage, grid, etc.) and a variable charge to fund grid operation (mainly fuel costs and maintenance). The variable charge could be very simple, updating it monthly or it could be more efficient, changing over time. The latter means using Time-of-Use rates or Real time – pricing, to dynamically adjust demand and supply, but needing a more sophisticated metering, telecommunication and information infrastructure, community's education and engagement. Isolated communities reactions to dynamic rates have been largely ignored in the literature, thus we do not factor this in our formulation. However, our model does provide spot values for electricity supply that can be used directly as price signals to fund the operation of the μG (*RTP* and *ToU*), similarly provides the investment annuity needed to size the connection fee of its clients.

In addition, in the novel methodology, investment payments must include capital payments and must remunerate risks involved (risk premium). In simple terms, rate of return must be high enough to cover financing and all the risks of the business.

This private-investor's perspective to estimate the rate of return is very common in developing countries, where governments have limited resources for these kinds of programs and thus the private participation is fundamental. Based on this reality we use a 10% rate of return, which we justify in detail further below and which depends on the reality of each geographical zone where the project will be deployed. Conversely, developed countries have generous budgets, easy access to credit at very low rates and their unsatisfied social needs are relatively low, which implies that projects may be evaluated with social discount rates at very low values (e.g., 4%, 6% or even less) and microgrids could be partially financed through subsidies.

The role of private investors in developing countries is fundamental and evidence suggests that they require higher rates at riskier realities, reaching rates as high as 20% for Jamaica in *LATAM*. For Chile, rates of 11.9% and 10.2 % have been calculated for hydroelectric and wind energy projects respectively using the *WACC* methodology, although most projects use 10% together with some UN Clean Development Mechanism projects (Watts, Albornoz, et al., 2015).

Normally, in developing countries additional penalties to discount rates exist when reliability standards are not met. These penalties usually do not impact rates and are incorporated, for example, through the Value of Lost Load (*VOLL*). This is the method used in our study, although other formulations exist that are not included here and could incorporate risk through an increase of rates.

Additionally, in our study we have used the rate of return that would make any local utility indifferent on serving the loads of the isolated community installing a microgrid with respect to the alternative of investing, administrating, operating and maintaining any distribution system in Chile. In Chile, the electricity service law sets a discount rate of 10% for any project in the transmission and distribution systems. In relation to the project of designing, constructing and operating a microgrid, any investor in distribution systems would be naturally interested in microgrids projects because of their similarities, which also justifies a discount rate of 10% for microgrids projects. Thus, any company contracted by the community could be interested in deploying a microgrid and obtaining long-term profit from this business while the community would have its electricity demands served.

3.3 Case Study: Colchane, an isolated community in the northern high plains of Chile, located next to the Bolivian border.

To show the application of the novel method proposed and to visualize the efficient trade-off between $LEFC$ and ENS, the isolated community of Colchane, located in the north of Chile and 2 km from the Bolivian border, was chosen. In this section, we describe the main characteristics of this community and its energy resources.

3.3.1 Main characteristics of Colchane: why is it interesting?

Colchane was chosen for this study because it has three very interesting and distinctive characteristics: i) it is an extremely isolated village with no access to electricity, ii) it is located in the Andes Mountain Range, which has low population density and geographic remoteness all across $LATAM$ and iii) it has very good local and renewable energy resources, wind and solar, with a high complementarity between them. As shown in Figure 3-5 wind is present at night and it peaks when solar radiation is quickly going down in the afternoon.

3.3.2 Colchane is an isolated community

The chosen site is located in the Andean high plains (latitude 19.28ºS& longitude 68.64ºW), northern Chile, 257 km from Iquique (the capital of the first region of

Chile) and less than 2 *km* from the border with Bolivia. This settlement has a population of 720 inhabitants (Williams lópez, 2010) - mainly indigenous Aymara - and corresponds to a border crossing, (thus it has all the usual facilities, e.g., customs and border control).

3.3.3 Colchane has a good renewable energy resource

Colchane's wind and solar energy resources are very good and complement each other during the hours of the day. Nevertheless, wind generation was corrected by the air density and *PV* generation by the air temperature, which are relativity low due to Colchane's extremely high altitude of 3722 mts. amsl. Its annual mean temperature reaches 6^oC (with extreme values of 19.3 and -8.4^oC during the year) and its mean air density reaches 0.81 kg/m^3 (approx. 2/3 of the normal sea level air density) (Chile, 2014a, 2014b) reducing potential wind production.

3.3.4 A typical mean Chilean load profile was chosen for the study

A typical static residential daily load profile for a densely populated urban area supplied with a cost-effective distribution system was chosen for this study - Santiago de Chile. This load profile represents the reference load of the hypothetical low cost Macrogrid, i.e. the highest level of consumption at the lowest cost.

The characteristics of such a load profile are: i) no air conditioning consumption (*A/C* is rare in *LATAM*), ii) a peak load consumption at the late evening hours (because people are home using lighting, *TV*, etc.), iii) a lower flat consumption during sun hours (since less people are home, lighting is generally not needed and activities are more uncorrelated, e.g., washing machine, iron, radio, computer, microwave oven.) and iv) decreasing consumption during the late night and early morning hours (because people are sleeping at home) reaching its minimum around dawn. This reference load profile can be seen in Figure 3-5.

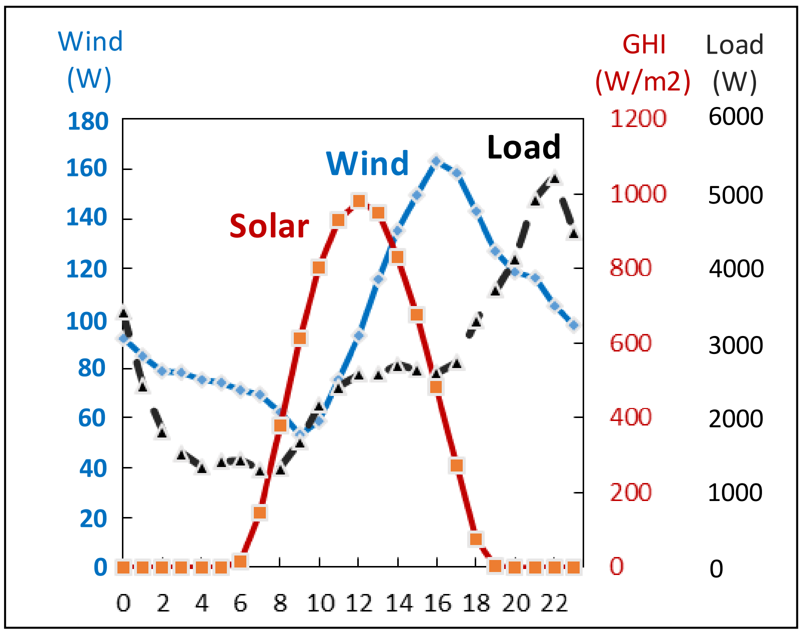


Figure 3-5: Solar and Wind resource complement each other well with load profile in Colchane from 10 *AM* in the morning to 8 *PM* in the evening. Load profile is typical for Chilean electricity consumers.

3.4 Models of the Distributed Energy Resources

The Distributed Energy Resources (*DER*s) typically used in a microgrid are modelled here, including diesel generators, gas micro-turbines, small wind turbines, photovoltaic solar panels and battery banks.

3.4.1 Small-scale wind turbine model using the power curve

In general, the power curve of a wind turbine can be used to model its performance and is usually published by the manufacturer. This curve indicates the power output of the turbine P_{WT} in relation to the wind speed V for a standard air density. Wind Turbines generate power for wind speeds above the cut-in wind speed v_{ci} (which produces the smallest torque that allows the turbine to rotate/generate) and below the *cut-out* wind speed v_{co} (maximum wind at which a wind turbine can operate without possible damage) (Manwell, McGowan, & Rogers, 2007).

For this work, the turbine AIR Breeze (Southwest Windpower, 2011a, 2011b) was chosen and has the following characteristics: i) a rated power $P_{WT_{nom}}$= 160W, ii) a cut-in speed of v_{ci} = 3.1*m/s*, iii) a cut-off speed of v_{CO} = 27.2 *m/s*, iv) a rated wind speed of v_r = 12.5*m/s* and v) a *DC* output power P_{WT}. The power curve used has a10 *min* integration interval and is valid from 0 to 27.2m/s (*Introducing Air Breeze*, 2009, *Solar Stik Marine Breeze Upgrade Kit ITEM # 005034*, 2011).

3.4.2 Photovoltaic panel

The electricity production of a photovoltaic or *PV* panel (P_{PV}) depends on the daily Global Horizontal Radiation (GHR_t), the gain associated with the angle of the solar panels R_{Gain}, its area A and its energy conversion efficiency (from radiation to electricity) η_{PV}(5). This efficiency can be further divided into the module's efficiency η_m and the efficiency of the rest of the plant (3.6) called Performance Ratio (*PR*). The latter depends mainly on the following deratings (3.7): a) power losses of nearby shadows η_{sh}; b) incident angle modifier η_{IAM}; c) module degradation η_{deg}; d) temperature η_{tem}; e) mismatch effect η_{mis}; f) soiling η_{soil}; g) wiring η_{mpp}; h) maximum power point η_{mpp} (Marion et al., 2005; Watts, Valdés, et al., 2015). The *PV* production P_{PV} and the efficiencies across the production chain are shown below.

$$P_{PV} = GHR_t \cdot R_{gain} \cdot A \cdot \eta_{PV} \tag{3.5}$$

$$\eta_{PV} = \eta_m \cdot PR \tag{3.6}$$

$$PR = \eta_{sh}\eta_{IAM}\eta_{deg}\eta_{tem}\eta_{soil}\eta_{mis}\eta_{net}\eta_{mpp} \tag{3.7}$$

PV module efficiency η_m at 25^oC and 1.5 *AM* can be expressed as shown in the following equation (Durisch et al., 2007),

$$\eta_m = p \cdot \left[q \cdot \frac{GHI}{GHI_0} + \left(\frac{GHI}{GHI_0}\right)^m\right] \cdot (2 + r + s), \tag{3.8}$$

where *GHI* is the Global Horizontal Irradiance, GHI_0 is a constant equal to $1000 W/m^2$ and the parameters are module specific. For this work, the module of

Kyocera LA361K51 was used with parameters p = 15.39, m = 0.0794, q = -0.177, r = -0.09736 and s= -0.8998.

Efficiency associated with temperature's derating effect on the module η_{tem} is calculated using the Normal Cell Operating temperature (*NOCT*) methodology (Duffie, n.d.; Notton et al., 2010),

$$T_c = T_a + \frac{GHI}{GHI_{NOCT}}\left(T_{NOCT} - T_{a,NOCT}\right)\left(1 - \frac{\eta_{Tref}}{\tau\alpha}\right) \tag{3.9}$$

$$\eta_{tem} = 1 - \beta_{ref}\left(T_c - T_{ref}\right), \tag{3.10}$$

where T_{NOCT} = 45ºC (obtained from a wind velocity v = 1m/s, $T_{a,NOCT}$ = 20ºC and GHI_{NOCT} = 800W/m^2), the efficiency of the module for the *NOCT* conditions is η_{Tref}= 0.127, the absorption coefficient $\tau\alpha$=0.9, $T_{ref} = 25°C$ is the reference temperature (at *STC*) and β_{ref}= 0.4% is the efficiency correction coefficient by temperature.

For the gain due to the optimum inclination of the photovoltaic panels the R_{gain} published by (Watts, Valdés, et al., 2015) for Calama was used, since this city is relatively close to the location studied (Colchane). In addition, the Kyocera module LA361K51 has a nominal power $P_{PV_{nom}}P$ = 51 W_p and an area of 98.5cm × 44.5 cm, which results in a per square meter installed power of 0.116 kW (nominal power used by the investor). Finally, an annual 0.5% degradation was used, and the other efficiencies were obtained from Watts (η_{sh}=98%, η_{IAM}=98%, η_{soil}=95.5%, η_{mis}=97%, η_{net}=99% and η_{mpp}=99%) (Norton et al., 2011; Watts, Valdés, et al., 2015).

3.4.3 Diesel Generator

The diesel generator modelled in this study can be either operating($X_{DG} = 1$)or shut-down ($X_{DG} = 0$). If it is operating, its output power P_{DG}can be regulated linearly from a minimum output power $P_{DG,min}$ to a maximum output power $P_{DG,max}$. If it is shut-down its output power is zero. No ramping up, ramping down, minimum uptime or minimum downtime restrictions are applied because of the small inertia of the generator and the large time interval used (of 1 hour) (Delaure & D'haeseleer, 2008; Viana & Pedroso, 2013). When the generator is operating, its output power will depend linearly on the diesel flowing into the combustion chamber F_{DG} (*m*^{3}/*h*), the efficiency of the generator η_{DG}, the lower heat value of the diesel LHV_D and the density ρ_D of this fuel as shown in the following equations:

$$P_{DG} = \frac{F_{DG} \cdot \eta_{DG} \cdot LHV_D \cdot \rho_D}{3600} \tag{3.11}$$

$$\mathrm{P}_{\mathrm{DG}_{\mathrm{min}}} \cdot \mathrm{X}_{\mathrm{DG}} \leq \mathrm{P}_{\mathrm{DG}} \leq \mathrm{P}_{\mathrm{DG}_{\mathrm{min}}} \cdot \mathrm{X}_{\mathrm{DG}}, \tag{3.12}$$

For Colchane the parameters used to design and operate the diesel generator are (min/max power, efficiency, heat value and density):$P_{DG_{min}}$=0.3$P_{DG,r}$, $P_{DG_{max}}$=1.0P_{DG_r}, η_{DG}=0.35 (*A Review of Distributed Energy Resources. New York Independent Operator*, 2014), LHV_D=42.791[*MJ/kg*] andρ_D=836.7 [*kg/m*^{3}], where $P_{DG,r}$is the nominal capacity rate of the generator (Greet, 2010).

3.4.4 Gas micro-turbine

The micro-turbine modeled in this study can either be operating($X_{TG} = 1$) or shut-down ($X_{TG} = 0$) (similar to the diesel generator model). If the gas generator is operating, its output power P_{TG} can be regulated linearly from a minimum output power $P_{TG,min}$ to a maximum output power $P_{TG,max}$. If it is shut-down its output power is zero. No ramping up, ramping down, minimum uptime or minimum downtime restrictions are applied because of the small inertia of the generator and the large time interval used (of 1 hour) (Delaure & D'haeseleer, 2008; Viana & Pedroso, 2013). When the generator is operating its output power will depend linearly on the gas flowing into the combustion chamber F_{TG} (m^3/hr), the efficiency of the generator η_{TG}, the lower heat value of the gas LHV_G and its density ρ_G as shown in the following equations:

$$P_{TG} = \frac{F_{TG} \cdot \eta_{TG} \cdot LHV_G \cdot \rho_G}{3600} \tag{3.13}$$

$$\mathrm{P_{TG_{min}}} \cdot \mathrm{X_{TG}} \leq \mathrm{P_{TG}} \leq \mathrm{P_{TG_{min}}} \cdot \mathrm{X_{TG}}, \tag{3.14}$$

For Colchane the parameters used to design and operate the gas micro-turbine are (min/max power, efficiency, heat value and density): $P_{TG_{min}}$=0.025$P_{TG,r}$, $P_{TG_{max}}$=1.0P_{TG_r}, η_{TG}=0.25 (*A Review of Distributed Energy Resources. New York Independent Operator*, 2014), LHV_G=47.141[*MJ/kg*] and ρ_G=1.25 [kg/m^3] @STC (Greet, 2010), where $P_{TG_r}$is the nominal capacity rate of the generator.

3.4.5 Battery bank

The Battery bank chosen is an aggregation of *AGM* lead acid batteries and is modeled as a lineal energy storage balance. In other worlds, the energy flowing into the battery system minus the energy flowing out has to be equal to the change in the energy storage (Faisal A Mohamed & Koivo, 2010).

In this model each battery has a maximum normalized charge and discharge current ($I_{BAT,max}$), a nominal voltage $V_{BAT,r}$, a charging efficiency $\eta_{BAT,c}$ when it is charged with a power $P_{BAT,c}$, and a discharging efficiency $\eta_{BAT,d}$ when it is discharged with a power $P_{BAT,d}$.

The battery bank possesses an upper load limit SOC_{max}, a lower load limit SOC_{min} and an initial state of charge SOC_{ini}. The model equations of the battery bank are:

$$P_{BAT_d} = (I_{BAT_d} V_{BAT_r} U_{BAT} N_{BAT})/\Delta t \tag{3.15}$$

$$P_{BAT_c} = (I_{BAT_c} V_{BAT_r} U_{BAT} N_{BAT})/\Delta t \tag{3.16}$$

$$SOC_t = SOC_{t-\Delta t} - (\eta_{BAT_c} P_{BAT_c} + \frac{1}{\eta_{BAT_d}} P_{BAT_d}) N_{BAT} \tag{3.17}$$

$$SOC_{min} \leq SOC_t \leq SOC_{max}, \tag{3.18}$$

where Δt is the time between measurements and t is the time of the measurement, I_{BAT_d} is the per unit discharge current, I_{BAT_c} is the per unit charge current and U_{BAT} is the battery capacity in Ah, $\eta_{BAT_c} = 0.75$is the charging efficiency and η_{BAT_d} is the discharging efficiency (which we consider equal).

The battery parameters for Colchane are $V_{BAT,r}$ = 12V, U_{BAT} = 150Ah, Δt = 1hr., $0 \leq I_{BAT_c} \leq I_{BAT_{max}} = 1$, $0 \leq I_{BAT_d} \leq I_{BAT_{max}}$, SOC_{ini} = 0.7SOC_{max}*and* SOC_{min} = *0.7*SOC_{max}. Note that N_{BAT} represents the number of batteries used as determined by the capacity optimization.

It should also be pointed out that the restrictions associated with *SOC* are intertemporal, which implies a particularly important effort for simulation since the number of variables used increases proportionally with the product between the number of devices (N_{DEV}) and the time intervals considered (N_t).

3.5 Robust Dispatch optimization: Mixed Integer Linear Programming considering worst load and renewable generation scenario

In this study the microgrid's operation is economically optimized in 2 steps: i) first, *PV* and wind Distributed Energy Resources (*DER*s) are dispatched due to their zero marginal costs (3.20) and ii) then the remaining net load $P_{NET\ LOAD}$ is supplied by dispatching all the different conventional *DER*s and Distributed Energy Storage Systems (*DESS*) efficiently. This optimization includes the capability of disconnecting conventional generation (diesel and gas) (3.21), usually known as the unit commitment (*UC*) problem. To make this model robust to the variability of renewable resources and load a Mixed Integer Linear programming (*MILP*) method was used taking into account the worst net load profile (which occurs with the maximum total load and the minimum *PV* and wind generation). Stochastic programming (*SP*) was discarded because of the difficulty to estimate load demand in a community that has never had any electricity consumption in the past, although it has been used in other studies to cope with renewable resources and load variabilities (Niknam, Azizipanah-Abarghooee, & Narimani, 2012). *SP* is known to be one of the most powerful optimization tools available but robust optimization (*RO*) reduces some tractability issues as recognized by Velasquez (Velasquez, Watts, Rudnick, & Bustos, 2016), in this case due to unknown load demand.

According to the original concept of Lasseter (Lasseter, 2002), each microgrid's *DER* has associated power electronics, which allows local control to stabilize the system without a centralized algorithm (using power vs. frequency droop and voltage vs. reactive power droop). Since loads of isolated communities in the desert (northern Chile) are relatively nearby, it is reasonable to assume relatively short distribution lines and thus negligible line losses. In addition, reactive power can be neglected due to power electronics and short lines.

3.5.1 Objective Function: minimization of fuel costs and cost of energy not supplied

The optimization is performed by minimizing the sum of all fuel consumptions and the cost of energy not supplied for each time *t*. Thus, the objective function is the total dispatch cost *DCost*:

$$DCost = \sum_t C_{DG} P_{DG} \Delta t + C_{TG} P_{TG} \Delta t + VOLL \cdot ENS_t \tag{3.19}$$

whereC_{DG} is the fuel cost of the diesel generator, P_{DG} is the power generated by the diesel generator, C_{TG} is the fuel cost of the gas microturbine, P_{TG} is the power generated by the gas microturbine, $VOLL$ is the Value Of Lost Load and $ENS_t = P_{F,t} \cdot \Delta t$ is the Energy not supplied in period t with respect to a reference Macrogrid.

3.5.2 Restrictions: *DER*, *DESS* and system restrictions are included in the model

Restrictions on the operation can be divided into *DER* restrictions, *DESS* restrictions and system restrictions. *DER* restrictions are minimum and maximum generation limits, and in-operation or shut-down status of conventional generation as well as PV and Wind turbine production models. *DESS* restrictions are battery charging and discharging limits and energy balance. The details of these restrictions and models are described in *Section 4:Models of the Distributed Energy Resources* and are as follows:

System restrictions are based on the balance of power between generators, batteries and load. Enough reserve was included implicitly in the demand to react quickly to its variations in time, while forced outages would immediately translate into larger values of unserved load. Keeping spare capacity is beyond community's budget in small microgrids of developing countries.

First, renewables are dispatched (obtaining the net load$P_{NETLOAD}$) and then conventional generation, together with the batteries, is balanced with $P_{NETLOAD}$. This is shown in the next equations:

1. Net Load: *PV* and wind generation has to be subtracted from the total load because they are dispatched at zero marginal cost.

$$P_{NET\ LOAD} = P_{LOAD} - P_{WT} - P_{PV} \tag{3.20}$$

2. Balance of Power: The sum of the power supplied by each *DER* or *DESS*, stored, failed to be supplied, and generated in excess should be equal to the Net Load.

$$P_{NETLOAD} = P_{DG} + P_{TG} + P_{BAT_d} + P_{BAT_c} + P_F + P_E \quad (3.21)$$

$P_{LOAD}$is the total power of the load, P_{WT} is the power generated by the wind turbines, P_{PV} is the power generated by the PV panels,$P_{BAT_d}$is the power discharged from the battery system, P_{BAT_c} is the power charged into the battery system$P_F$is the power failed to be supplied and P_E is the power lost through excessive over generation.

According to the convention used, all power injected into the load is positive P_F and must always be positive ($P_F > 0$) and P_E must always be negative ($P_E < 0$).

3.5.3 Diesel and gas fuel costs: prices and taxes in Chile

For the estimation of the diesel and natural gas fuel costs, public information and tax schemes are used. For diesel the mean public selling price of 502.1 *CH$/ltr*. (Chilean pesos per liter)for the 1stRegion of Chile registered by the National Energy commission of Chile is used (*Precios observados a Público: Promedios nominales en regiones y Región Metropolitana (Precio Diesel, Octubre)*, 2015). Similarly for natural gas a price of 497 *CH$/m^3* @ *STC* for the 1st Region is used (*Precios observados a Público: Promedios nominales en regiones y Región Metropolitana (Precio Gas Natural, Octubre)*, 2015). These low prices correspond to October 2015, which incorporates the recent international price drop of oil.

Both diesel and natural gas fuels have specific taxes according to Chilean law ("Chilean Law 18502: Establishes taxes to specific fuels," 2013)and are as follows: i)Diesel is taxed with 1.5 *UTM/m^3* and ii) gas with 1.93 *UTM* each 1000m^3.Nevertheless,for diesel there is a special mechanism in place that allows reimbursement of this tax ("Chilean Law 20258," 2008, "Circular Nr. 22 del 11 de Abril de 2008. Devolución del impuesto específico al petróleo diesel a la sempresas generadoras eléctricas," 2008). Thus, in our evaluation diesel was calculated without this tax.

Additionally, an exchange rate of 700 *USD/CH$*, *UTM* of 44776 *CH$* and a *VAT* of 19% was used (*VAT* was included in all prices).

3.6 *DC* & *AC* microgrid configurations

The cost of power electronics in microgrids is relevant and must be included. Nevertheless, different configurations with different equipment can be found. *AC* microgrids(based on *AC* electrical grids) are the most widely used configuration today, but *DC* microgrids (based on *DC* grids) are increasingly gaining interest, e.g., because they do not need synchronization and have no reactive power (Unamuno & Barrena, 2015). Both configurations along with hybrid *AC/DC* configurations (some mix of both) have different advantages and flaws regarding technology costs, reliability and maturity, which are widely discussed in the literature without reaching consensus (Backhaus et al., 2015; Justo, Mwasilu, Lee, & Jung, 2013; Karabiber, Keles, Kaygusuz, & Alagoz, 2013; Kramer, Chakraborty, Kroposki, & Thomas, 2008; Patrao, Figueres, Garcerá, & González-Medina, 2015; Planas, Andreu, Gárate, Martínez de Alegría, & Ibarra, 2015; Staunton & Ozpineci, 2003).

For the case study presented in this study only *DC* and single phase *AC* microgrids are possible because three-phase grids are not feasible at the 0 to 8 *kW* power range used. Thus, if the application would be scaled up (e.g., aggregating several households), a three-phase grid would be eventually needed.

3.6.1 The configuration that minimizes cost is chosen (*AC/DC* configurations are discarded because they are immature)

In this study we choose the *AC* or *DC* configuration that minimizes the total cost of power electronics for a given generation technology mix, i.e. inverters, chargers, converters, relays and any other control for the proper operation of the microgrid. We also assume that loads are all *AC* (which is standard in *LATAM*) and a load sharing control is always present, although some small home-systems are using full *DC* supply appliances. *AC/DC* configurations are discarded because they need a *DC/AC* converter that allows bidirectional power flow, which is an immature technology that is not available on the market – as far as we know (Jin, Loh, Wang, Mi, & Blaabjerg, 2010; Loh, Li, Chai, & Blaabjerg, 2012; She, Huang, Lukic, & Baran, 2012).

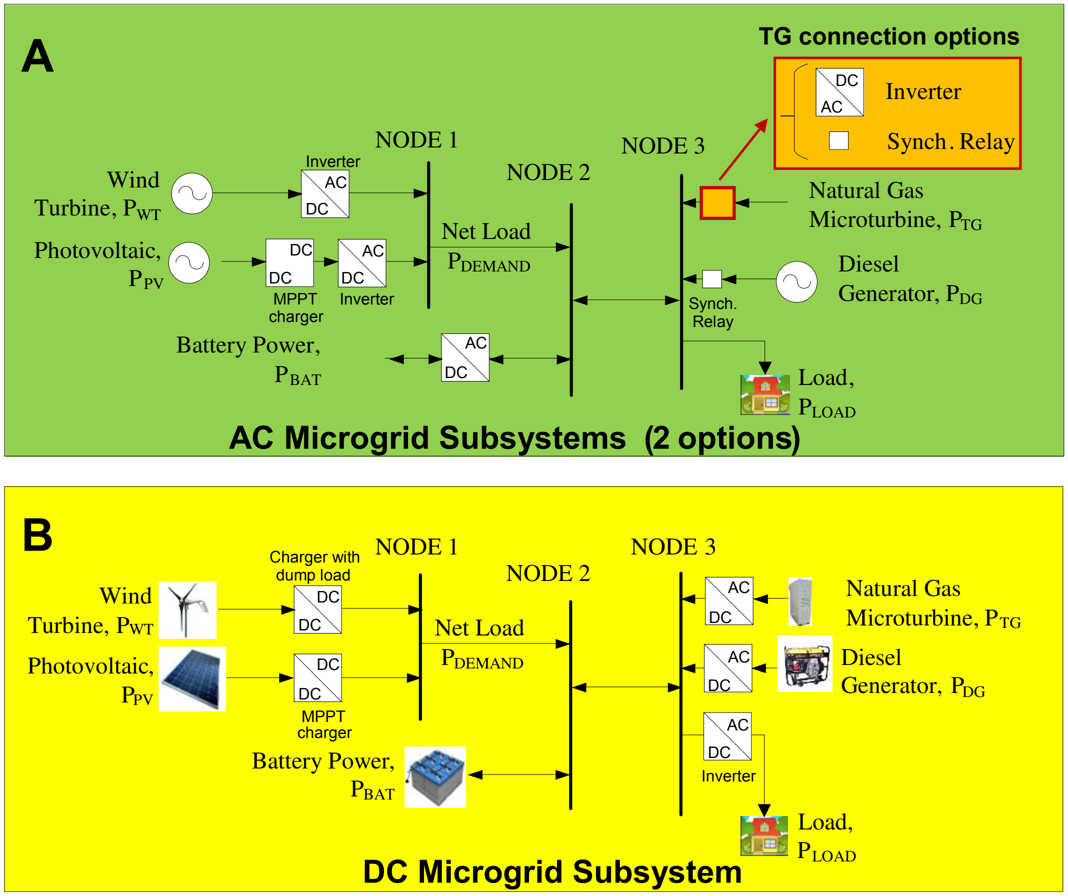


Figure 3-6: Microgrid *AC* or *DC* configuration options. A) *AC* configurations: two (2) options for the connection of the gas micro-turbine (*TG*) to the grid (with an inverter when *TG* is *DC* and with a synchronization relay when *TG* is *AC*. B) *DC* configuration.

3.6.2 *AC* configuration description

Two *AC* configurations are considered: i) one with a gas micro-turbine (*TG*) connected to the *AC* grid using a synchronous relay (“MME AC power concept,” 2014, “MME C30AC Microturbine data sheet,” 2014) and ii) one with a *TG* connected to the *AC* grid using an inverter (“MME C30DC Microturbine data sheet,” 2014, "*MME DC* Power Concept," 2014). The configuration that uses a synchronous relay is more frequent than the one using an inverter because *TG* typically has an *AC* synchronous machine and thus an *AC* output voltage.

In all *AC* configurations, *PV* panels and wind turbines are connected to the *AC* grid through individual inverters and batteries are connected through an *AC/DC* charger (because *PV* panels and batteries, as well as wind turbine model AIR40, have *DC* output voltages). In order to improve efficiency, *PV* panels are considered with Maximum Power Point Tracker (*MPPT*) capability. Both alternative *AC* configurations can be seen in Figure 3-6a.

3.6.3 *DC* Configuration description

The only *DC* configuration considered is based on the idea of having one battery charger for each generator. Thus, wind turbines are connected through *DC/DC* battery chargers because the wind turbine model used (AIR Breeze) only has a *DC* output. *PV* panels also have *DC/DC* battery chargers but with extra *MPPT* capability. Conventional generation (diesel synchronous generator and gas micro-turbine) are connected using *AC/DC* chargers. Finally, one additional inverter is needed to convert from the *DC* grid voltage to the *AC* load (Figure 3-6b).

3.6.4 Cost model of configurations

The cost model of both *AC* and *DC* configurations (2 *AC* and 1 *DC*) are expressed as the summation of the cost of each individual technology. For each technology, the cost is assumed proportional to its capacity, implicitly assuming limited economies of scale at the range of capacity of this study[16]. This is shown in the following equations (3.22 - 3.24):

AC configuration with TG using inverter:

$$EC_{AC1} = C_{Inv}P_{WT} + (C_{MPPT} + C_{Inv})P_{PV} + C_{Ch}P_{BAT} + C_{Syn} \cdot 1 + C_{Inv}P_{TG} + C_{LoadShare} \tag{3.22}$$

AC configuration with *TG* using synchronization relay:

$$EC_{AC2} = C_{Inv}P_{WT} + (C_{MPPT} + C_{Inv})P_{PV} + C_{Ch}P_{BAT} + C_{Syn} \cdot 2 + C_{LoadShare} \tag{3.23}$$

DC configuration:

$$EC_{DC} = C_{Ch4WT}P_{WT} + C_{MPPT}P_{PV} + C_{Ch}P_{TG} + C_{Ch}P_{DG} + C_{LoadShare} + C_{Inv}P_{LOAD} \tag{3.24}$$

In equations (3.22 – 3.24) C_{Inv} is the cost of the inverter per unit of capacity, C_{MPPT} is the cost of the Maximum Power Point Tracker (*MPPT*) converter per unit of capacity, C_{Ch} is the cost of the battery charger per unit of capacity, C_{Syn} is the cost of a synchronization relay, $C_{LoadShare}$ is the cost of a Load Sharing control and C_{Ch4WT} is the cost per unit of capacity of a battery charger with dump load designed for the use of wind turbines.

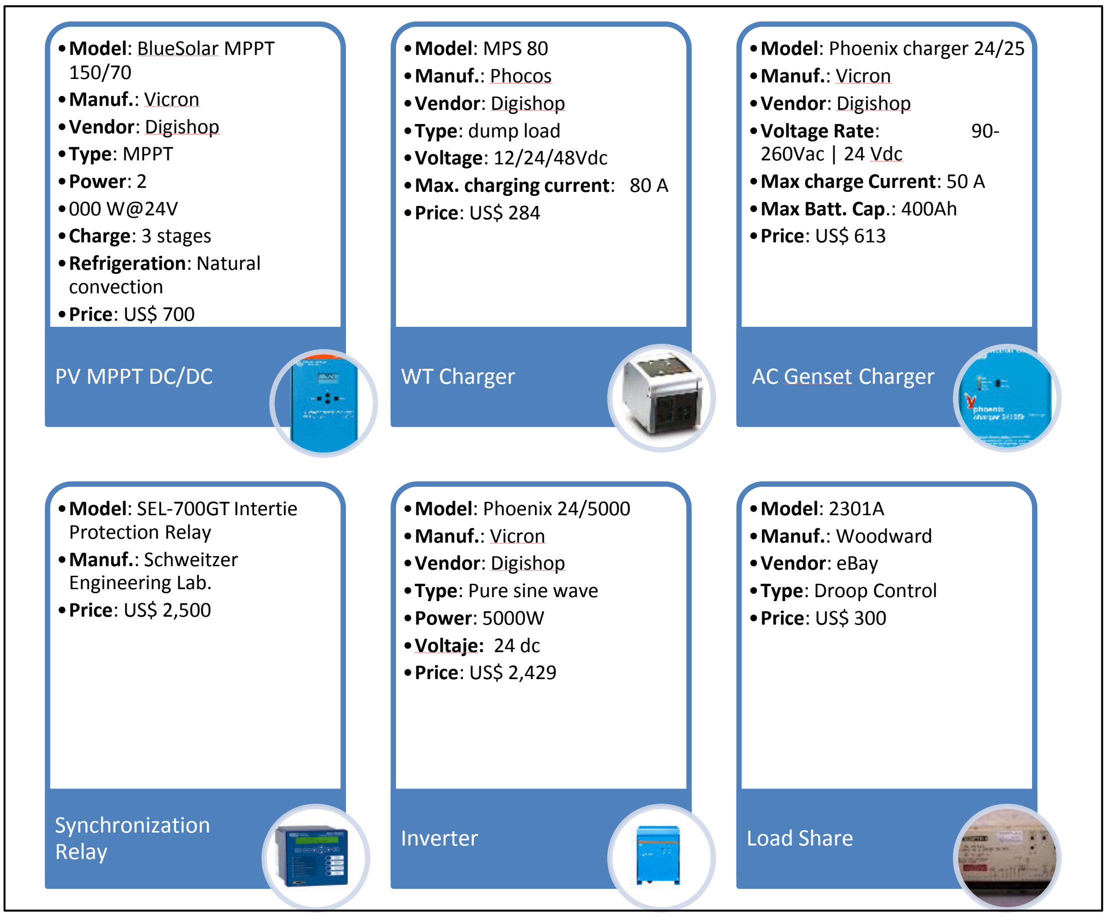
[16] This assumption is not strong because most systems under study in Chile, Bolivia or Peru are small communities with few dozen people, always below a few hundred kW.

3.6.5 Configuration cost estimation: based on equipment available on the market

The cost of each *AC* or *DC* configuration is based on the sum of power electronic components. To use realistic costs, each component was quoted in the market for each configuration, then its unit price per *kW* was used. The details of each equipment, including brands, models, specifications and prices can be seen in Table 3-1 and are the following.

- Maximum Power Point tracker (*MPPT*): Specific *DC/DC* converter for *PV* panels used in all configurations
- Charger with dump load: Specific battery charger for wind turbines, which maintains load when over-generating in *DC* configurations.
- Inverters: pure sine wave inverters used for i) loads in *DC* configuration (loads assumed *AC*) and ii) for Wind turbines, *PV* systems and micro-turbines in *AC* configurations.
- Synchronization relay: For diesel *AC* gensets (in this case prices were considered for each relay (not per *kW*).
- Load sharing control: For all configurations. Equipment quoted is for *AC* configurations. For *DC* configurations, the same cost was assumed.

Table 3-1: Detail of power electronics quoted for the different *AC* and *DC* configurations. Information includes brands, models, technical specifications and price



3.7 Capacity Optimization Trade-off Model

The trade-off for isolated microgrids between the Levelized Cost of Energy + energy Failed to be supplied *LEFC* and the Energy Not Supplied with respect to a reference Macrogrid ENS_{mM} can serve as a valuable tool for communities to choose the microgrid design (i.e. technology mix, operation and configuration) that best fits their particular needs from a minimum cost set. It is critical that this set has an endogenous *VOLL* to avoid suboptimal lower cost estimations, which corrects the traditional methodology found in many textbooks.

3.7.1 Trade-off: Multi-objective optimization of the nominal capacities of each technology solved using Genetic Algorithms

To find the efficient frontier of the trade-off, a multi-objective optimization was defined for *LEFC* and ENS_{mM} using the installed capacity rate of each technology as control variables (Diesel generation *DG*, gas micro-turbine *TG*, Batteries *BAT*, wind turbines *WT* and photovoltaic panels *PV*) restricted to upper and lower installed capacity limits for each technology. This was solved finding the set of Pareto optimal microgrid technology mixes, using genetic algorithms (*GA*).

3.7.2 Optimization problem formulation

The trade-offs a set of pairs of 2 functions in conflict $\mu G = LCOE + F(\vec{P}_{nom}), ENS_{nM}(\vec{P}_{nom})$ that are minimized when they fulfill the Pareto optimality, i.e. when improving one criterion means worsening the other. In terms of capacity optimization formulation, the trade-off model is as follows:

$$\max_{i\epsilon\Omega} \mu G(i) = \{LCOE^{i}(\vec{P}_{nom}), ENS^{i}_{mM}(\vec{P}_{nom})\} \quad (3.25)$$

and the restrictions are:

$$\vec{P}_{nom} = [P_{DG_r}, P_{TG_r}, SOC_{BAT_r}, P_{WT_r}, P_{PV_r}] \quad (3.26)$$

$$0 \leq \vec{P}_{nom} \leq P_{LOAD_{max}}, \tag{3.27}$$

where Ω is the feasible solution space and the variables to be optimized are the nominal capacity rates of each technology: for diesel generation, for the gas micro turbine, for the battery bank, for the wind turbines and for the *PV* generation. P_{DG_r} is the maximum output power of the diesel generator, P_{TG_r} is the maximum output power of the gas turbine, SOC_{BAT_r} is equal to the maximum Storage capacity of the battery ban. P_{WT_r} is the nominal power of all N_{WT} windturbines, considering the nominal power of a single windturbine is equal to $P_{WT_{nom}}$= 160 *W* as stated by the manufacturer (which is approximately equal to the maximum output power of the wind turbine averaged each 10 minutes according to *NREL* procedure). Finally, P_{PV_r} is the nominal output power of all N_{PV} *PV* panels, considering the nominal power of a single *PV* panel equal to $\mathrm{P}_{\mathrm{WT}_{\mathrm{nom}}}$= 51 *W* as stated by the manufacturer.

Relating the decision variables of (3.26) to the variables described in section 4 we can say that:

$$\text{Diesel generator: } P_{DG_r} = P_{DG_{max}} \tag{3.28}$$

$$\text{Gas micro turbine: } P_{TG_r} = P_{TG_{max}} \tag{3.29}$$

$$\text{Battery bank: } SOC_{BAT_r} = SOC_{max} \tag{3.30}$$

$$\text{Wind turbine: } P_{WT_r} = P_{WT_{nom}} N_{WT} \tag{3.31}$$

$$\text{PV system: } P_{PV_r} = P_{PV_{nom}} N_{PV} \tag{3.32}$$

3.7.3 Pareto optimality

When two objective functions are in conflict (e.g., $LEFC$ and ENS_{mM}) every pair of microgrid mixes has two possibilities: i) one is preferred over the other or ii) neither is preferred. In particular, it is said that a feasible microgrid mix $\mu G(i)$is preferred over another $\mu G(j)$ (with $i \neq j$) when it is lesser in at least one criterion and it is not greater in the other ($\mu G_i \prec \mu G_j$), i.e. when one of the following conditions is fulfilled

$$LEFC^i \prec LEFC^j; ENS^i_{mM} \preccurlyeq ENS^i_{mM} \tag{3.33}$$

$$LEFC^i \preccurlyeq LEFC^j;ENS^i_{mM} \prec ENS^i_{mM} \tag{3.34}$$

Additionally, one feasible mix $\mu G(i)$is said to be non-dominated with respect to space of feasible solutions Ω when there does not exist any other mix $\mu G(j)$, such that $\mu G(i) \prec \mu G(j)$, i.e. when improving one criterion means worsening the other criteria, producing a trade-off between both. Such microgrid mixes are called Pareto optimal and form the Pareto set. The values of the objective functions ($LEFC$ and ENS_{mM}) for all the Pareto optimal mixes form the Pareto front. Thus, the main objective of a multi-objective optimization is to find the Pareto set.

3.7.4 Assumptions for the calculation of the Levelized Cost of Energy plus the Cost of Energy Failed to be supplied

For the calculation of *LEFC,* the following costs and assumptions are used to represent the "average" cost that a commercial project could face in Chile:

- Fuel costs and cost of energy not supplied (*F*): Calculated by the optimal dispatch (see section *5. Robust Dispatch optimization*),
- Capital costs of each *DER* and *DESS*(Table 3-2),
- Replacement costs of each *DER* and *DESS* (Table 3-2),
- Operation and Maintenance (*O&M*) costs ex-fuel of each *DER* and *DESS* (Table 3-2),
- Lifetime of each *DER* and *DESS* (Table 3-2),
- Discount rate of 10% (Watts, Albornoz, et al., 2015),
- Microgrid expected lifetime: Evaluation horizon of 20 years,
- Power electronic costs: Calculated as the minimum cost choice from a set of predefined AC or DC configurations (see section *6. DC & AC microgrid configurations*),
- Contingencies and Balance of Plant (*BOP*) costs: added on top of investment costs (10%).
- Project management, project development and logistics costs: added on top of investment costs (10%).
- Inland terrestrial transportation costs: These are almost negligible because of the particularities of Colchane (around *USD* 100 for the whole system). It is located 230 *km* from Chilean harbor of Iquique (230 *km*) and has an excellent access route[17].

[17] Terrestrial Transportation costs are particularly low for Colchane. Its price was quoted in the market and corresponds to the cost of transporting a small microgrid of less than 10 kW from the harbor of Iquique to Colchane following a path of 230 *km* and using a small truck. The truck was calculated to be large enough to transport any of the possible microgrid designs, thus the transportation cost is always equal for any possible microgrid from the efficient Pareto frontier.

Table 3-2: DER and DESS costs. Capital, replacement and O&M. Also their expected lifetime is indicated

DER Type	Refe-rence	Investment Costs			Annual O&M Cost (non-fuel)[19]		Life-time
		Unit	Capi-tal	Reposi-tion	Unit	Value	[years]
Diesel generator	a	USD/ kW	900	756	USD/ kWh	0.014	4
Gas turbine	a	USD/ kW	1500	900	USD/ kWh	0.010	2
EV's Battery Bank	b	USD/ Wh	250	192	USD/ kWh	13	5
Wind Turbine	c	USD/ kW	6260	N/A	USD/ kW	90	20
PV Panel	d	USD/ kW	2000	N/A	USD/ kW	20	25

[a] (*A Review of Distributed Energy Resources. New York Independent Operator*, 2014)
[b] (M. Arriaga, Cañizares, & Kazerani, 2013; Matteson & Williams, 2015; York, 2014)
[c] (Orell & Foster, 2015)
[d] (*A Review of Distributed Energy Resources. New York Independent Operator*, 2014; Watts, Valdés, et al., 2015)

3.8 Results: electricity cost-coverage trade-off including for each optimal microgrid its design type, capacity mix, optimal dispatch, cost composition, and configurations

The results presented in this section show that the range of optimal isolated microgrid designs, from which the community of Colchane in the northern high plains of Chile

[18] No se incluye el costo de combustible, que se trata separado en la sección *3.5.3. Diesel and gas fuel costs: prices and taxes in Chile*

can choose, is huge. In total 176 Pareto optimal microgrid designs were found, all of which compose the cost-coverage trade-off. The most reliable microgrid is 100% more costly than the one with the least coverage, including the cost of the energy not supplied.

In the following subsections for each optimal microgrid design, its capacity mix, daily economical dispatch, cost composition and configuration (DC or AC) are detailed.

3.8.1 A microgrid is preferred over another when it is less costly and has more electricity coverage

Each feasible microgrid design has its own particular electricity cost and coverage. The cost of each possible microgrid design is determined by its optimal capacity mix, its optimal economic dispatch and the power electronics' configuration of minimum cost, including investment costs, operational costs and the cost of energy failed to be supplied. In this study electricity coverage is measured by $1 - ENS_{mM}$, where $ENS_{mM}$is the per unit measurement of the Energy Not Supplied of a microgrid *m* relative to an ideal Macrogrid M. ENS_{mM} is partly due to a conscious decision of the community and partly due to the reduction in consumption of an unreliable supply (Figure 3-2).

To find the best microgrid designs, the Pareto optimality criteria was applied to the electricity cost and coverage. Levelized Energy and Failure Cost *LEFC* was preferred to compare costs, and Energy Not Supplied ENS_{mM} was preferred to compare electricity coverage ($LCOE$ was discarded because it does not includes the cost of energy failed to be supplied). Nevertheless, $LCOE$ was also calculated because it represents the monetary cost a community will have to pay. An example of how to use the Pareto criteria is shown in Figure 3-7. Here a microgrid x_1 is preferred over another microgrid x_2 because it simultaneously has a lower $LEFC$ and less ENS_{mM} .In this particular case, less ENS_{mM} for x_1 means also less $LEFC$, which explains the preference.

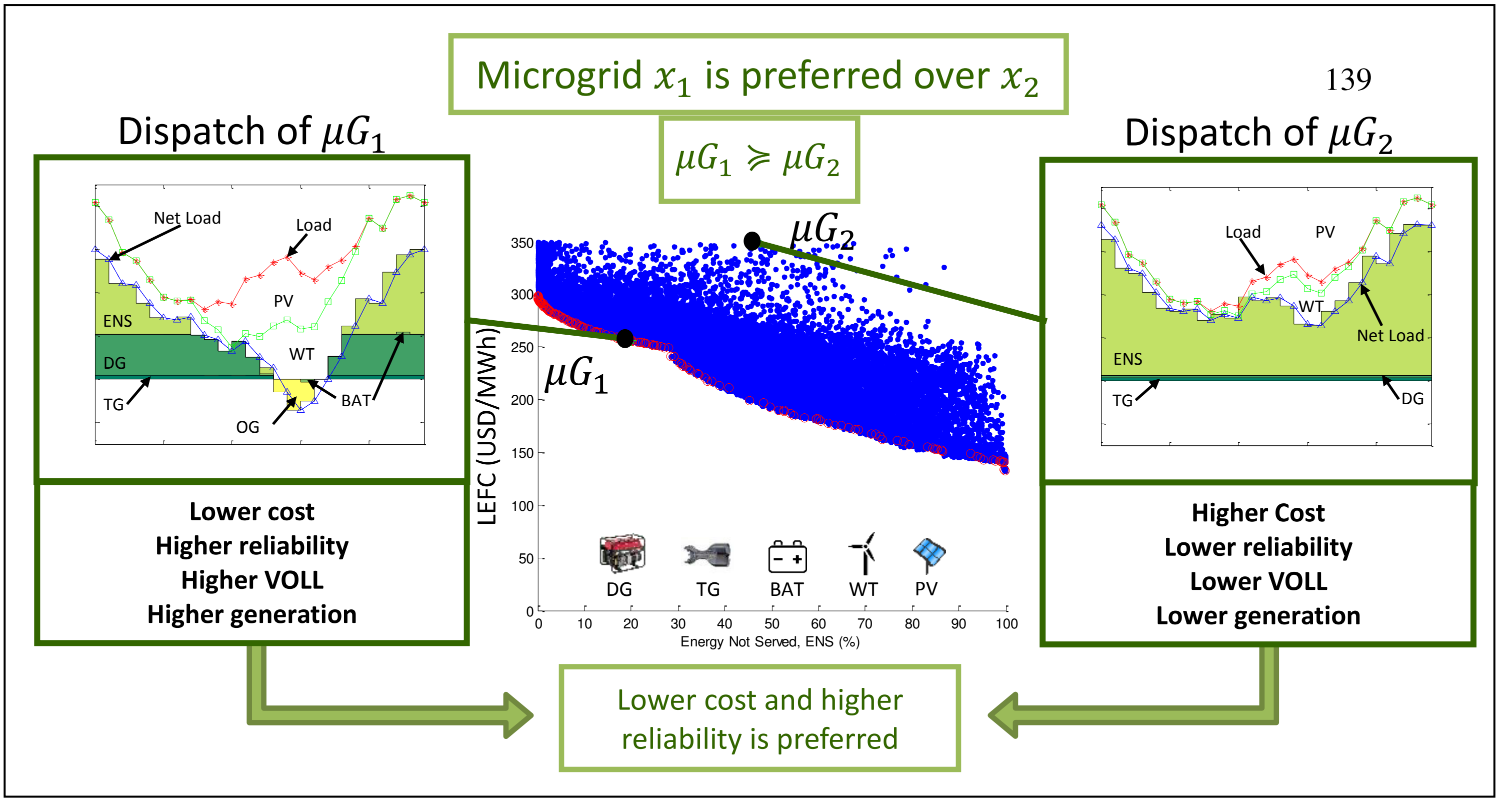


Figure 3-7: Example of a microgrid x_1 that is preferred over a microgrid x_2 ($\mu G_1 \succcurlyeq \mu G_2$). This is the case, because microgrid x_1 has less Energy not Supplied (*ENS*) it is less costly and more reliable than microgrid x_2.

3.8.2 *LEFC* Results: Feasible, impossible and optimal microgrid's tehcnology mixes

The impact of the cost-coverage trade-off on communities is very significant because of the large range of microgrid designs found. The 176 Pareto optimal solutions obtained for the isolated community of Colchane in the northern high plains of Chile have a decreasing *LEFC* with increasing ENS_{mM}, starting at *298 USD/MWh* and 0% ENS_{mM} and ending at 133 *USD/MWh* and 100% ENS_{mM}. All microgrid mixes above and to the right of the optimal solutions are feasible but suboptimal, i.e. they are more costly and less reliable. All mixes below and to the left of that solutions are unfeasible, i.e. they have impossibly low costs and high electricity coverage combinations (see Figure 3-8, in which all blue points correspond to all feasible mixes found by the genetic Algorithm).

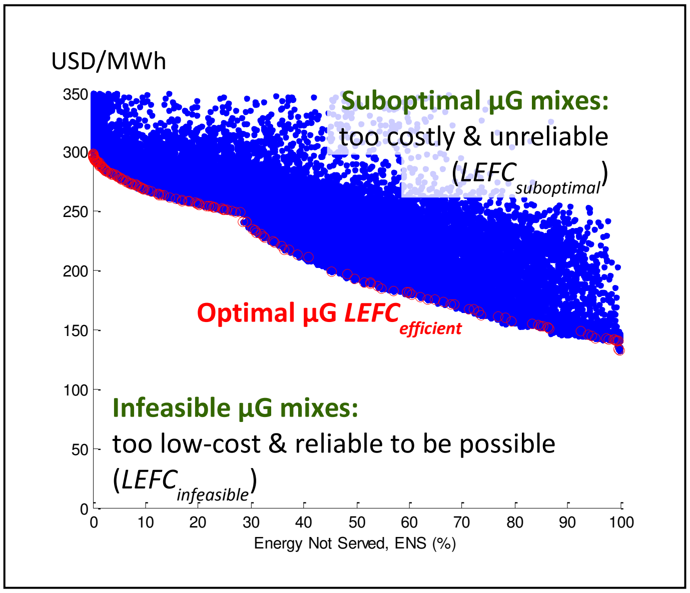


Figure 3-8: Feasible (suboptimal), infeasible and optimal microgrid mixes. Lower-left curve is the Pareto efficient frontier (red), which contains all optimal microgrid mixes. Al feasible and suboptimal microgrid mixes are located above and to the right (all blue points correspond to all suboptimal solutions found by the genetic Algorithm). Below and to the left of the optimal Pareto frontier unfeasible microgrid mixes would be located, i.e., such low cost and high reliability combinations are impossible to achieve.

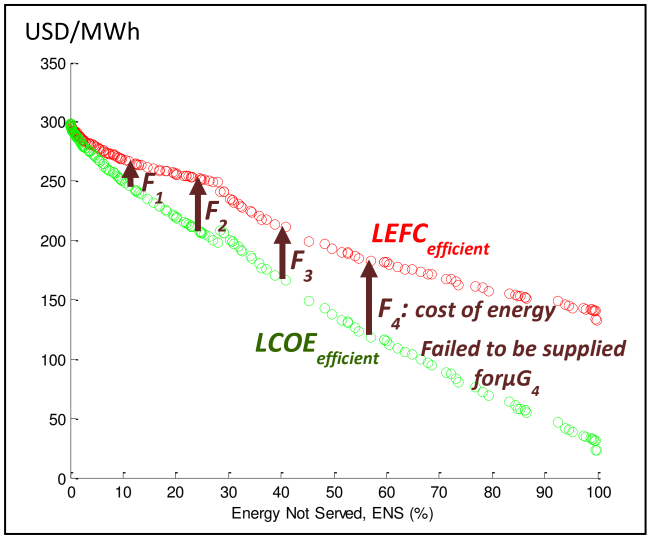


Figure 3-9: Levelized Energyand Failure Cost (*LEFC*) and Levelized Cost Of Energy (*LCOE*) for the case of the isolated community of Colchane in Chile.

3.8.3 *LCOE* results: the actual expenditure the community will have to make.

LCOE is relevant because it represents the actual expenditure the community will make per unit of energy. The difference between *LEFC* and *LCOE* is the cost of energy Failed to be supplied *F*, which usually increases with diminishing electricity coverage. In general, *LCOE* decreases when ENS_{mM} increases, starting at 298 USD/MWh for 0% *ENS* and finishing at 23 USD/MWh for 100% *ENS*. One exception exists at 28%*ENS*, where a discontinuity marks a change from hybrid mix type of microgrids (conventional and renewable energy resources) to a renewable only mix type (wind and *PV* energy resources only) as detailed further below. At this exceptional discontinuity *LCOE* rises and the cost of energy Failed to be supplied *F* falls. (see Figure 3-9).

3.8.4 Microgrid types identified: two higher quality and hybrid mix types and two lower quality and renewable only mix types

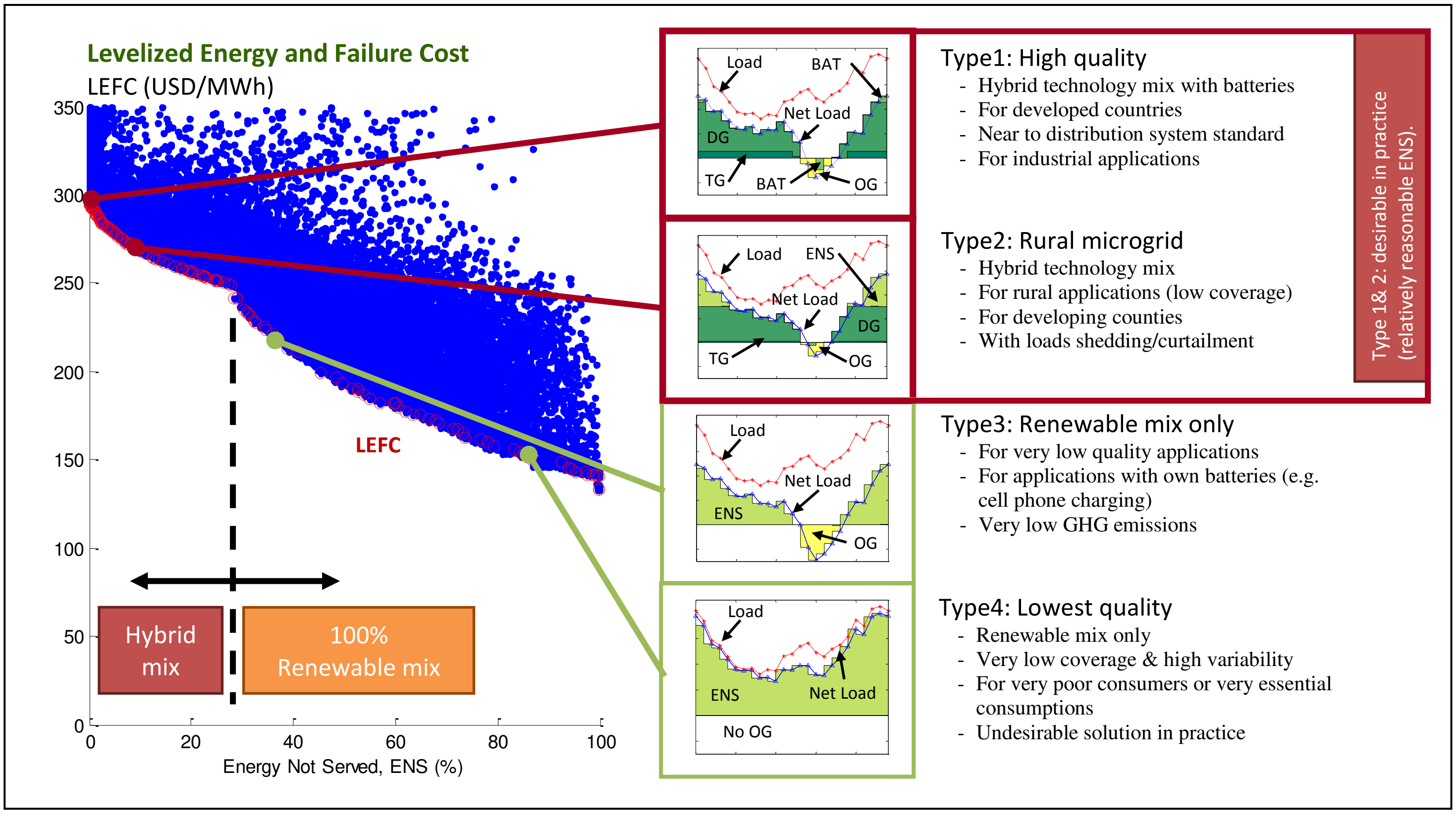


Figure 3-10: The four types of microgrids identified for Colchane. These types can be further aggregated into microgrids with hybrid technology mixes (with conventional and renewable energy resources) and 100% renewables. The two most reliable/costly microgrid types have hybrid technology mixes and the less reliably/costly have renewable-only mixes. The hybrid technology mix types are desirable in practice due to a relatively acceptable *ENS*.

From the Pareto optimal microgrid designs 4 main types of microgrids where distinguished, ranging from high-quality/high-cost to very-poor-quality/very-low-cost designs (see Figure 3-10) depending of their electricity cost and coverage. From these four types, the two most reliable/costly microgrid types have hybrid mixes (conventional and renewable energy resources) and are desirable in practice since their ENS_{mM} is still relatively reasonable (less than 28%). More ENS_{mM} is impractical in most cases such as those obtained from the two least reliable/costly microgrid types which have mixes based entirely on renewable energy resources. Nevertheless, these less reliable microgrid types can be complemented with the owner's batteries in applications such as cell phone charging or electric vehicle charging (for example in temporary military bases). All microgrid types are dicussed briefly as follows, considering their potential application in places with similar conditions as Colchane, but eventually located in developing countries or in developed ones:

Type 1 - High quality microgrids

This type of microgrid has high electricity cost/coverage microgrids with near distribution system standards. They have a hybrid mix including batteries to shift peak load. Isolated communities using this kind of system are probably wealthy and/or have critical loads (e.g., in developed country or for industrial applications).

Type 2 - Rural microgrids

These are less reliable (but also less expensive) than the Type 1 High Quality microgrids. They use hybrid mixes but do not use batteries. Cost is reduced by curtailing peak loads and they can be applied to rural applications or in developing countries where communities are modest but loads are close.

Type 3 – Renewable mix only microgrids

These are systems with very low electricity coverage, which are very low cost as well. Their mixes are renewable only (with overgeneration) and thus have very low Green House Gas (*GHG*) emissions. Because of its intermittency, applications will probably need batteries from the owner (e.g., cell phone charging, electrical vehicle charging).

Type 4 – Lowest quality microgrids

These are the worst quality microgrids and thus the lowest cost ones. They are based only on renewable energies and have no overgeneration. These are, in general, very undesirable solutions because of the large intermittency of renewables. Batteries would be needed as in the case of Type 3 microgrids – Renewable mix only microgrids.

3.8.5 Microgrid capacity supply curve

The capacity supply curve was obtained for each generation technology, i.e. diesel, gas, wind and *PV* energy resources (Fig 11 upper row of graphs). Diesel and gas based generation is only present in the most reliable hybrid microgrid types (Type 1 – high quality microgrids and Type 2 – rural microgrids). Wind generation is present in all four types of microgrid designs, increasing its installed capacity when *LEFC* increases. Just when the microgrid design changes from a renewable-only mix to a hybrid (conventional + renewable) mix, wind installation falls sharply. *PV* generation will be installed less for decreasing ENS for the most reliable microgrid types (Type 1 – high quality microgrids and Type 2 – rural microgrids) and more for decreasing *ENS* for the least reliable microgrid types (Type 3 - renewable only microgrids and Type 4 – lowest quality microgrids).

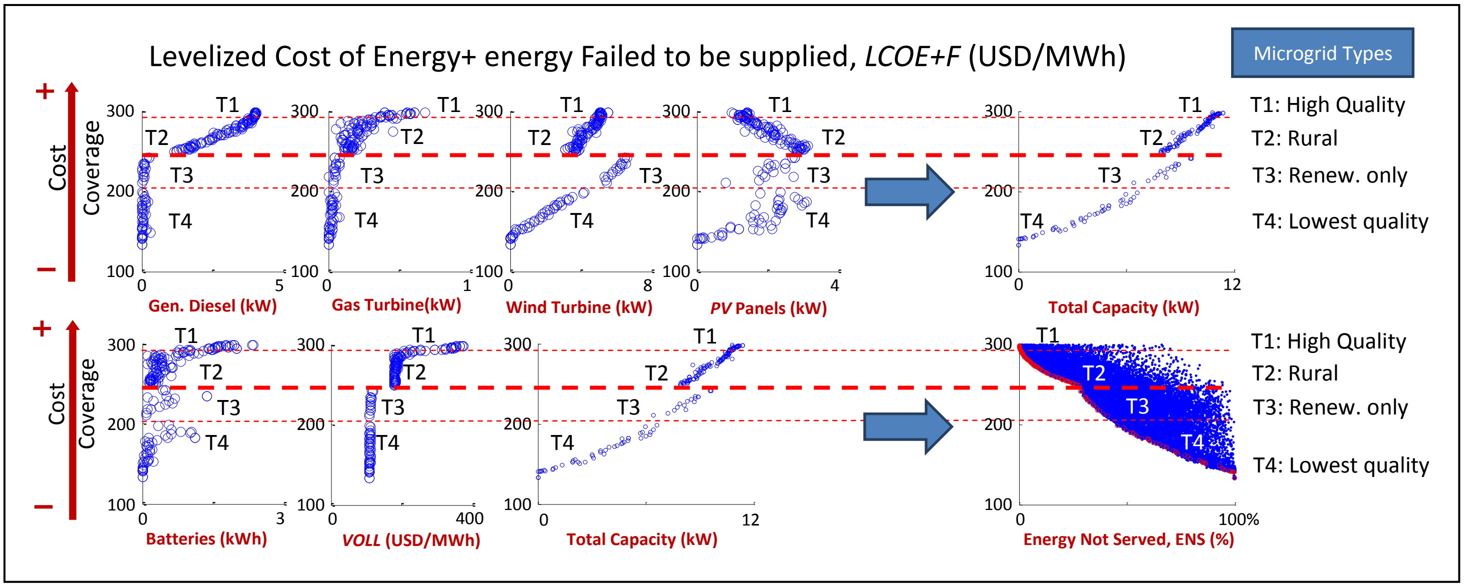


Figure 3-11: Cost decomposition of capacities and Value Of Lost Load (*VOLL*) for each microgrid type. First Line: Generation capacity supply curve is constructed from diesel, gas wind and *PV* generation. Second Line: Batteries, *VOLL* and capacity supply curve imply the cost-coverage trade-off curve.

The capacity curve obtained shows that less capacity is needed for the same electricity cost and coverage when conventional generation replaces renewable generation. This is due to the larger plant factors of conventional energy resources.

3.8.6 Batteries: very few and only to shift load

Batteries are installed only on very high-quality/high-cost microgrids (Type 1) and in small amounts to shift peak load with renewable energy overgeneration (Figure 3-11 lower left graph). For all cases, the maximum total installed capacity is always less than 3*kWh*, which is less than two batteries (of 12*Vdc* and 150*Ah*).

Since storage technologies are still expensive (battery cost assumption is near 250 *USD/MWh*), our model did not install massive amounts of *DESS*. Storage investment is triggered whenever a very valuable arbitrage opportunity is found ("buying cheap energy to sell it expensive"). This means charging with solar and wind power (0 *USD/MWh*) and shortly after injecting back that power, reducing costly demand failed to be supplied (e.g., *VOLL* equal to 300 *USD/MWh*). Since diesel is relatively cheap in the example area, batteries are only justified to reduce energy non-supplied in very short time periods, avoiding fuel costs and investments at peak loads (similar to demand side management or critical peak pricing events).

3.8.7 *VOLL*: Increasing with electricity coverage and very sensitive to high quality microgrids.

In general, the Value Of Lost Load (*VOLL*) increases with higher cost/coverage microgrids (Figure 3-11 lower row, second column of graphs). Nevertheless, for high quality (Type 1) microgrids *VOLL* is highly sensible to electricity coverage. For all other types *VOLL* is almost (not completely) constant and presents a discontinuity between Type 2 and Type 3 microgrids (because of a change from a hybrid technology mix to one based only on renewable energy).

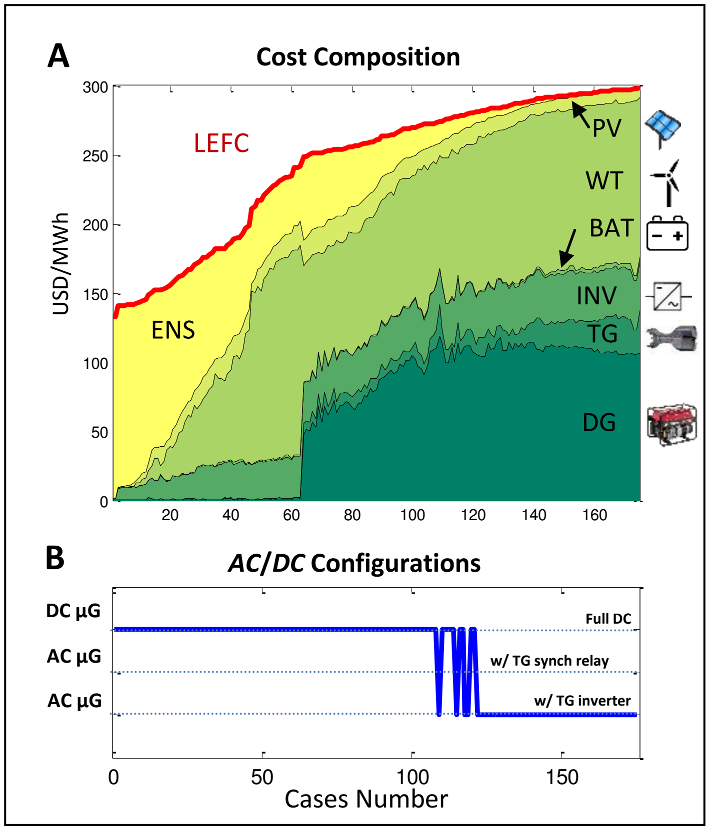


Figure 3-12: Cost decomposition and optimal configuration for each of the Pareto optimal microgrid mixes. A) Levelized Energy and Failure Cost (*LEFC*) decomposition. B) Minimum cost configurations chosen.

3.8.8 Cost decomposition: Wind, diesel and energy not supplied are the main cost drivers.

Two cost composition types exist for all Pareto optimal microgrid designs depending on their mix is renewable only (lower quality) or hybrid (higher quality) as seen in Figure 3-12a.

In lower quality microgrids, the cost of energy failed to be supplied, as well as wind generation costs, is very important. Both the cost of *ENS* decreases and the cost of wind generation increases with increasing electricity coverage. Second order costs are the cost of power electronics (*AC* or *DC* configuration) and cost of *PV* generation. No conventional generation or batteries exist for these microgrids.

For high quality microgrids, which have hybrid technology mixes, diesel and wind energy resources are the most significant costs. Power electronics, gas turbo-generator and *PV* are second order costs. Cost related to *ENS* decreases with higher electricity coverages.

3.8.9 Configurations: *DC* is preferred for small installed capacities and *AC* for large installed capacities.

Higher cost/coverage microgrids have more installed capacities as can be seen from Figure 3-12b. *DC* configurations are preferred for small capacity microgrid mixes, due to their lower fixed cost (e.g., no sync relays)and larger variable costs (which depend on installed capacities, e.g., load inverter). *AC* configuration are preferred for large capacity microgrid mixes, due to larger fixed costs (e.g., synch relays) and lower variable costs (that depends on installed capacities, e.g., no load inverter). Between both *AC* configurations, the one with an inverter is preferred over one with a synchronous relay at the gas turbogenerator's output because *TG*'s capacity is always less than 5.2 *kW* (which is the flipping point between both solutions).

3.9 Conclusions

3.9.1 The problem: lack of access to electricity and consumption restriction due to high costs or low coverage of consumption

Today, the welfare of 1.1 billion people around the world is severely affected by their lack of access to electricity. Despite electrification efforts made during last decades, a large number of isolated communities, located in places where the cost of extending the distribution grid is too expensive, face a supply dilemma. These communities are still disconnected from the electrical system, are provided with electricity through very unreliable grids, or are supplied partially at very high costs, only for some critical loads, a few hours a day, through stand-alone generation (usually diesel generation).

These inadequate high-cost/low-coverage power supply systems restrict the consumption of communities massively depriving them of electricity and its benefits. A more precise methodology is needed to assess whether it is socially beneficial to supply electricity to those communities and to which extent. This means formalizing the fact that communities will not be served entirely (100%) but it is probably suitable for them to receive lower levels of electricity coverage at cheaper rates that consider their willingness-to-pay.

In the long term, communities are required to find their own particular electricity cost-coverage equilibrium, which will confront their needs of reducing costs and increasing coverage. The full range of optimal microgrids that can be offered to a community is a trade-off between cost and coverage from which the community can choose a tailor made design that best suits their particular needs. The curve resulting from this trade-off can be obtained optimizing simultaneously both objectives using the Pareto optimality criterion.

3.9.2 A novel methodology that offers the best supply microgrids possible for the isolated community to choose from:

By developing a novel methodology, this study contributes to solving the problem of restricted access or even no access to electricity in isolated communities due to high costs or low coverage of consumptions. This novel methodology delivers a list of different microgrid designs simultaneously optimized for cost and coverage using the Pareto optimality criterion. Each of these designs adjusts to a particular need of electricity coverage and economical budget for the community in question. Their capacity, configuration (*AC* or *DC*) and Economical Dispatch are also optimal, and are found with a three-stage strategy.

3.9.3 Rural electrification programs can benefit from a microgrid approach:

Rural electrification programs can benefit strongly from a microgrid-based approach to assess energy supply for isolated communities. Its advantage over a technology specified *a priori* (as they do today much too often) is that microgrids contain all specific technology mixes, including the possibility of a single technology supply (e.g., diesel generation or *PV* systems). This allows the distributed energy resources to compete and complement each other depending on their nature, which allows the community to benefit from lower costs. For example, *PV* and storage complement each other and compete with diesel because more batteries allow the installation of more *PV* panels, shifting the produced energy to peak load hours and displacing diesel generation.

3.9.4 Current electricity cost-coverage trade-off methodologies are corrected endogenizing the Value Of Lost Load:

This novel methodology also contributes to correct today's literature on the use of electricity cost-coverage trade-offs by endogenizing the Value Of Lost Load (*VOLL*), which is the cost per unit of energy not supplied (*ENS*). Current methodologies simply use a constant and *a priori* fixed *VOLL*, which we show is suboptimal and underestimates the total cost including the cost of energy failed to be supplied.

3.9.5 Two classes of microgrid mixes found for Colchane: Expensive/high quality vs. cheap/low quality.

In particular, the impact of the new methodology for the example case of Colchane is very significant. A large range of costs and electricity coverages were found, numerous optimal microgrids designs were calculated (176 in total) and two different microgrid classes of nature and application were identified: i) a expensive but high quality class with wide applications in isolated communities and ii) a cheap but low quality class only applicable when complemented with demand side measures such as batteries (like cell phone or electrical vehicles in the future). Below we describe the major findings regarding these classes.

Colchane, a very interesting place to study, is located in the northern high plains of Chile on the border with Bolivia. It is representative of low population areas far away from the central Macrogrid (typical of the Andes and the Amazon regions). In addition, it has very good wind and solar resources, which complement each other very well with the typical Chilean load profile.

a) Findings for expensive/high quality microgrid class

The main finding for places with the load profiles and climate conditions considered for Colchane is that expensive/high quality microgrids with average electricity coverage of 86%, technology mixes are hybrid (conventional and renewable) with an almost linearly decreasing relation between cost and coverage (slightly convex). For these microgrids, the main costs are related to diesel and wind generation. Total costs (*LEFC*) range from 298 *USD/MWh* to 249 *USD/MWh* for *ENS* from 0% to 28%[19], which have practical applications in almost all isolated communities (e.g., high quality microgrids in developed countries, lower quality microgrids for developing countries or for rural applications, industrial applications, etc.).

From these high quality microgrids, we further identify two different types which are as follows:

i) High quality microgrids

Microgrids with the highest cost and with almost 0% *ENS*, renewable overgeneration and very small battery banks shaving peak load.

ii) Rural microgrids

lower cost microgrids with less than 28% *ENS*, renewable overgeneration but without batteries.

[19] including the cost of energy failed to be supplied

b) Findings for cheap/low quality microgrid class

A second finding for places with Colchane's climate and load conditions is that there are potentially interesting applications for lower quality, renewable-only microgrids, only feasible when willingness-to-pay is low(e.g., solar pumps). For their class, these applications do not require continuous supply or are complemented with other solutions. These microgrids are incredibly cheap but almost ridiculously unreliable, having nearly linear decreasing relations (slightly convex) between supply cost and electricity coverage. Their cost is typically just above hundred US dollars per kWh with coverages around 60% (from a cost of 133 *USD/MWh* to 241 *USD/MWh* and *ENS* from 100% to 28%). Main costs are related to wind and *ENS*.

High levels of unsupplied energy are easily tolerated by a lot of isolated communities in developing countries as they already have either no supply (100% *ENS*) or and expensive supply which forces them to consume only a few hours a day (e.g., 40 to 60% *ENS*). Another potential application source are low quality microgrids and critical loads equipped with pre-existing batteries, such as cell phones, rechargeable batteries for radios and television, laptops or even *EV*s, which are sunk cost due to other needs (e.g., communication, transportation). An example of these applications could be military bases or outdoor explorations. Another source includes loads that could welcome interruptible low cost supply whenever available, e.g., pumping systems.

From these lower quality microgrids, we further identify 2 different types which are as follows:

i) Renewable energy only microgrids

This type of microgrid is impractical in most cases (not all) with very low costs, very poor electricity coverage and renewable overgeneration

ii) Lowest quality microgrids:

This microgrid type is impractical in most cases (not all), lowest cost/coverage and without overgeneration.

3.9.6 Beyond this study

The access to electricity through the deployment of microgrids in isolated countries is not a technical engineering problem anymore. The main difficulties are now in the economical, sociological and political arenas. For the matter of a microgrid's economy, this paper carefully addresses the supply side of the microgrid, its cost and its reliability. However, a lot more research is needed. On the demand side, the characterization of the potential composition of loads of those communities without electricity supply, their appliance ownership and level of usage in communities with very expensive supply still remains a challenge. Moreover, there is a need for research on consumption priorities when budget is highly constrained and energy takes an important proportion of the budget. On the social and political side, it is still unclear what kind of organizational approach is best to secure the long-term sustainability of a microgrid in relation to the social context.

Financial literature addresses different portfolio mixes for finding the efficient risk-return frontier, which is only useful if this is shown to investors with well-known risk aversion or risk-taking behavior. Matching both sides allows giving each investor the best return he can get for the risk he is willing to take. This paper addresses different microgrid mixes finding an efficient Pareto optimal frontier between supply cost and supply coverage. Nevertheless, in finding the optimal microgrid, the community, which has to pay for it, needs to understand its budget, socioeconomic conditions, resources, lifestyles and other factors to allow inferring a willingness-to-pay for electricity coverage and the associated load profiles.

The methodology proposed in our work can be extended (although at times it can become an intractable problem), moving from a static approach of demand to a dynamic one, thus covering its discrete growths. This is achieved by implementing, in a first stage, the methodology as described in the manuscript to design a greenfield microgrid. Then, in a second stage, it is possible to expand the system to cover the new loads. At this stage, the existing microgrid should be maintained and new capabilities and technologies covering incremental loads should be included, considering the joint operation of the microgrid. During this expansion it is also possible to retrofit the required community coverage, offering a Pareto-efficient frontier for expansion using, for example, Genetic Algorithms (*GA*). Finally, for future increases in demand, it is simply necessary to repeat what was described in the second stage (to expand the microgrid of the previous stage and to readjust the coverage).

As the electricity consumption of the community growths, a connection to the Macrogrid becomes more feasible (the investment costs of the interconnection feeder get divided by a larger energy volume). Moreover, traditional distribution networks typically increase their coverage area over time, therefore the interconnections of microgrids and Macrogrids become more likely over time. These equilibria are very specific to each community's geographical condition and its isolation, thus there is a limited treatment of this in the literature.

We emphasize that there is little research on how consumption is evolving in an isolated community, so there is a strong need to continuously monitor their use of facilities, new needs, growth, and consumption explosion when a new industry is installed or the opposite when removed (e.g., a mining company in the north of Chile or a sawmill in the south). This is very different from a macrogrid where the growth is quite predictable and is on the order of 2 or 3% for Chile. In the micro-grid of an isolated community, there may be potential growths of 40% or more from one year to the next, so the traditional planning schemes applied in the macro-grids are usually applicable in these cases.

Our work seeks to recognize that the success and failure of a microgrid depends strongly on the context in which it is implemented (cultural, social, economic and technical). That is, in order for the probability of success of a microgrid to increase, the particular reality of the microgrid must be recognized and that means that whoever is the owner, manager and / or operator of the network must design something that the community can afford and that meets their needs. In that sense we do not intend to give a prescription of who should decide what demand should be covered for which community, but offer a wider range to whoever makes the decision. However, we believe that it is fundamental that whoever makes the decision must understand very well the reality and the needs of the community, since it is precisely their willingness to pay and their satisfaction that will decide whether it is sustainable over time.

4 EXPLORING TARIFF DESIGN UNDER MASSIVE RESIDENTIAL DISTRIBUTED ENERGY RESOURCES: PV AS A GAME CHANGER

4.1 Introduction

4.1.1 Distribution Systems are changing in developed countries and developing countries are starting to follow.

In developed countries around the world life of electricity end-users is being transformed due to changes in their electricity supply (e.g., the *USA* and Europe). For example, they have been increasingly producing green electricity from their own *DERs*, self-consuming and injecting their surplus to the grid (e.g., using *PV*). Also, they have been choosing their electricity retailer thanks to newly installed smart-meters ("Choose Energy Acquires Power2Switch," 2013, "Compare The Best Texas Electricity Providers," 2017; Hunt, 2013; Yadack et al., 2017).

In general, these changes at the electricity end-user level are mainly driven by new environmentally friendly people and policies present in developed countries. These new drivers are usually supported by budgets that are large and durable enough to incentivize the market expansion of new technologies (e.g., *DERs*), which has translated into dramatic reductions of per-unit costs (e.g., through *learning-by-doing* or technology breakthroughs (Rubin et al., 2015)). Although developing countries may not be capable to develop these incentives due to other more urgent social priorities, *DERs* could be deployed massively in the future if these drops of technology costs would fall below grid-parity, which is starting to happen in some countries like Chile.

4.1.2 Distributed Energy Resources are at their tipping point to reach grid-parity at some markets without financial support due to their significant cost reduction.

The electricity industry is witnessing dramatic costs reductions of clean technologies, both at the utility scale and for Distributed Energy Resources (*DER*) at the end-user scale. For example for the 2008 - 2014 period, wind, distributed *PV*, utility-scale *PV* and Batteries have shown cost reductions between 73 and 41% (Pérez-Arriaga & Knittel, 2016). As a consequence, these technologies have become mainstream energy suppliers, penetrating wholesale markets thanks to financial or government incentives,(*Global Wind Report, Annual Market Update*, 2016; Tim Shear, 2016; Wirth & Schneider, 2017).

Recently, PV panels have managed to penetrating wholesale markets without incentives thanks to their continuously falling costs by reaching grid-parity in a few countries with outstanding solar resources. If cost continues to fall, many other countries would probably reach grid-parity in the future, making country's specific solar resources and incentives each time less relevant.

Examples of these new revolutionized markets are Chile and Middle East & North Africa (*MENA*) countries. The former is the rising star in renewable energies with world’s cheapest solar energy production without subsidies. In these places, PV-bid-offers were registered in 2016 at values as low as 29 *US$/MWh* for Chile (Final

Report of holesale electricity bid, refered to by article 131 of Chilean Electricity law, 2016) and later on 24 *US$/MWh* for Abu Dhabi (Pothecary, 2016). At the end-user scale, *PV* has shown similar cost-reduction trends for small-scale applications (Wirth & Schneider, 2017). In fact, grid-parity for commercial and industrial clients with consumptions large enough to justify rooftops larger than 10 kW was achieved in Chile one or two years ago. Here, residential grid-parity is more challenging to achieve, because small rooftops do not face the same economies of scale. Nevertheless, regarding cost-reduction trends, it is reasonable to think that small-scale residential *PV* systems could also reach grid-parity in some countries, especially in places with high solar resources (Chung et al., 2015; Schmalensee, 2015).

Batteries are another technology that are dropping their costs at a high speed for end-user applications. Lithium Ion batteries (Li-Ion), in particular, are expected to revolutionize electricity distribution systems by allowing electric vehicles (*EV*) economical integration (technical and economical feasibility), which could happen within the next 10 years ("Electric Cars to Reach Price Parity by 2025," 2017; Lowe, Tokuoka, Trigg, & Gereffi, 2010). In general, Li-Ion battery costs were reported to be round 300 - 400 *USD/kWh* the year 2015 (Nykvist & Nilsson, 2015) (Neubauer, Brooker, & Wood, 2013) , although according to some manufacturers Li-Ion batteries could soon reached prices below 100 *USD/kWh* due to groundbreaking research ("BioSolar Prototype Demonstrates Clear Path to High Capacity, Low Cost Lithium-Ion Battery," 2015). Whether this claim becomes truly available in the market is to be seen.

In addition to *PV*, wind and Li-Ion batteries, costs are dropping for other *DER* technologies as well. In general costs related to Information and Communication Technologies (*ICT*) have shown descending trends during the last decades (Schaller, 1997), which may impact other intelligent devices such as smart-meters and smart inverters.

4.1.3 Distributed Energy Resources' cost reduction and market growth are expected to continue in the foreseeable future

Rapidly falling technology costs for *DER* are explained by several factors, which keep pushing costs downwards and could thus enable the entrance of new services for the end-user, revolutionizing the way we experience energy. Among these factors literature has highlighted the ability of the industry to learn from its own experience, i.e., *learning-by-doing* (Rubin et al., 2015) (Swanson, 2006). For example, *PV* panel costs have fallen over 20% each time its installed capacity has been doubled during the last few decades and Lithium Ion (Li-Ion) batteries have fallen between 6% and 9% under the same conditions (Nykvist & Nilsson, 2015). These rates are called *experience* or *learning rates* and their resulting learning curves are empirical laws of cost reductions (Rubin et al., 2015). *Learning rates* are good mid- to long-term predictors (de La Tour, Glachant, & Ménière, 2013) and may be used together with production estimates to forecast future price trends.

Thus, if disruptive market changes, due to a probably increasing world market for *PV* systems, happen only with small impacts, constant price drop could be expected for future years, although one should always keep in mind that markets cannot grow indefinitely in the long-term, as they eventually achieve maturity.

Assuming *learning rates* will keep constant, new countries, such as Chile, may reach grid-parity at the distribution level, which could open new markets for *DERs*. These new markets could accelerate the world's global capacity growth rate of *DERs* and thus costs could fall even sharper, while the financial burden of low-carbon incentives could be - at least partially – released. On top of these trends, unpredictable technology breakthroughs have to be added, which would just push costs even further down.

In conclusion, if market conditions remain nearly the same, cost-reduction-trends are expected to continue in the future for *DER* technologies due to the capacity of the industry to learn-by-doing. These trends could be sped up due to the opening of new markets and technology breakthroughs.

4.1.4 Impact of a high penetration of residential *DERs* and tariff design on distribution system's customers, utilities and regulators.

High penetration of residential *DERs* in distribution grids heavily impact end-users' electricity bills and thus may imply significant financial risks for utilities and other end-users without the capacity to invest in such projects. These impacts may cause social, political and social problems, which should be avoided by the regulator. Thus, it is critical to find a regulation that treats all end-users and utilities in a fair and economically efficient way, despite the game-changing penetration of *DERs*. Therefore, different tariff designs should be explored and the impacts on each type of stakeholder (i.e., end-users and utilities) should be quantified. Depending on the regulator's actions, benefits of the new energy services offered by *DER* to end-users could get lost - at least partially - calling for good regulation practices.

Considering current regulation in several countries, massive deployment of residential *DER* could heavily increase distribution system charges to customers because distribution companies' (discos') revenues - in a large proportion - come from selling electricity at a volumetric per unit energy charge that bundles generation costs, network tariffs and policy costs (especially to households), the latter surprisingly important in some countries. That is, the total investment, *O&M* and administration cost of the distribution system would have to be paid for by less consumed electricity units if a large number of customers would install their own *DER,* thus increasing grid's per-unit-energy-charges. If utilities were not allowed by the authority to rise charges (e.g., because utilities' remuneration processes do not endogenize *DER* penetration) or if *DER* penetration develops too fast and authorities are not capable to react in time (e.g., because of a regulation's rigidity), distribution companies would be put at a higher bankruptcy risk (i.e., increasing their probability of not recovering their costs). Conversely, if the utility is allowed to raise their tariffs in synchrony with *DER*'s deployment, the utility-revenue-problem could be solved. Nevertheless, if tariffs rise end-users would be encouraged to deploy *DER* even further, which in turn may increase tariffs again. This cycle is called in literature the distribution system *Death Spiral* (*DS*) (I. P. Arriaga et al., 2014; Sioshansi, 2016), which is a positively reinforced loop that could eventually be unsustainable, maybe ending with the disconnection of the end-user.

The impact of Death Spirals (*DS*) on residential low income consumers compared to high income ones could be different. This difference may represent some risk to themselves, regulators and utilities. This is especially important in countries where income differences (e.g., measured by the Gini Index) are sharp, which happens more often in developing countries. Among these developing countries the *LATAM* region stands out due to its particularly high inequality, shown by high Gini Indexes (Montecinos & Watts, 2015) ("GINI index," 2015). Thus, especially in developing countries *DSs* could encourage higher income consumers to deploy *DER*, leaving on average, a lower consumer supplied by the grid. Depending on income, different impacts can be expected because consumers with a higher income are more likely to have the budget or credit capacity to finance *DER* investments. Thus, the rise of distribution system charges produced by *DSs* would impact mainly low income electricity end-users, which are usually worse payers than higher income consumers.

A potential solution to DSs, although somewhat controversial, is to separate the volumetric per energy-unit electricity tariff into at least two parts: i) a charge for the option of using the grid, which would add up utilities' revenues and ii) a per energy-unit tariff, which would pay for the cost of generating each energy unit. This tariff separation would decouple the electricity consumption of each consumer from the cost of having the grid, assuring steady revenues for the utility and solving the *DS*-problem by eliminating the need to raise tariffs.

Nevertheless, if regulation changes are not done on time, separating tariffs to decouple the cost of the grid from the electricity consumption may also represent a risk for *DER* owners. For *DER* owners regulation changes due to a high *DER* penetration are risky because they may represent a change of rules that could have made *DER* unfeasible at the moment of investment. For example, if the regulator would change tariffs' structure from a volumetric energy tariff to another that decouples the cost of the grid from the energy consumed, then the residential *DER* owner would save considerably less by self-consuming its own electricity production, and thus would have to pay the grid cost separately. If *DER* penetration is high (e.g., 50%), then the customers' dissatisfaction would rise abd become a political risk to the regulator. Thus, regulatory changes should be made ideally before *DER* penetration begins, or at least at its very early stages.

In summary, to avoid costs and risks for the regulator, utilities and end-users (of both high and low income) a potential solution is to decouple tariffs into one part that reflects the cost of the grid and another that represents the cost of the electricity unit consumed. In addition, the change in tariff structure has to be done before *DER* penetration begins or at least at its very early stages.

4.1.5 Importance of a robust worst case scenario approach to understand the maximum impact of *DER* penetration and tariff design on utilities and customers due to the impossibility to assess *DER*'s speed and intensity of customers' adoption.

It is nearly impossible to accurately assess how fast and how many customers will deploy *DER* once they become economically attractive. Adoption rate estimation is a big challenge itself. Nevertheless, for tariff design and economic regulation it is of vital importance to be prepared for all possible scenarios. This can be done by considering the one scenario that has the highest impacts on all economic agents (e.g., utility and customers), i.e. using a robust worst-case tariff design. In this study, the worst-case scenario was assumed when all customers adopt *DER* at the same time, inelastically, and immediately after reaching grid-parity, because it would have the most rapid and massive impact on society. A robust approach that deals with these worst-case scenarios could give great insight into possible customer response to tariff changes and falling *DER* prices, as well as to the utility's bankruptcy risk.

International experience of residential *PV* deployment in Europe shows that its adoption is often very rapid, demanding a careful preparation of the grid and regulation for this scenario. For example, in Spain Feed-in-Tariff (*FiT*) was introduced in 2007, and that same year, around 500 *MW* were installed, followed by over 2000 *MW* in 2008, becoming the world's largest *PV* market in the world that year. Something similar happened in Italy where more than 9 *GW* where installed in 2011, and in France and the *UK* where more than 1 *GW* was installed in each of those countries in 2012 (EurObserv, 2007, 2009, 2010, 2011, 2012).

4.1.6 Grid-parity: The key variable for end-user adoption.

In general, a large body of literature can be found for residential *PV*, where economic assessment in general, and grid-parity in particular, is regarded as the key variable for customer adoption (Breyer & Gerlach, 2013) (Van Benthem, Gillingham, & Sweeney, 2008; Zhai & Williams, 2012). After grid-parity is reached, the probability of *DER* adoption increases dramatically. Even more, after grid-parity is reached and costs of *PV* panel continually drop, adoption probably will keep rising due to an improving economic evaluation. Interesting is the study of Zhai, who finds out that adoption probability is quite high in relation to grid-parity for Phoenix, Arizona. Without end-users concerned about maintenance, adopting probability is always above 40% at grid-parity and could reach as high as 100% depending on environmental concerns (Zhai & Williams, 2012).

Beside grid-parity, there are other variables affecting DER adoption which relate to consumers' particular costs and preferences. These variables are usually difficult to assess, such as hidden costs (Yang, 2010), environmental concerns (Zhai & Williams, 2012), social networks (Jager, 2006), adopter categories (Faiers & Neame, 2006), technology diffusion (Van Benthem et al., 2008) and the cognitive bias of human beings (Frederiks, Stenner, & Hobman, 2015; Kahneman, 2011). For example, hidden costs should normally be included into the cost of PV systems such as maintenance costs, upfront costs, complexity perception, and aesthetics (Yang, 2010), but they are sometimes difficult to quantify and predict, especially for household applications. Additionally, cognitive biases and motivational factors may explain economically irrational behavior of human beings (i.e., deviations from a standard rationality), which are studied by behavioral economics (Kahneman, 2011). A list of these biases applied to household energy decision-making can be found in (Frederiks et al., 2015). All these complementary variables can slow-down or accelerate the adoption of *DERs* but are probably much less significant than grid-parity.

We make a separate mention for electric cars and all possible services that are related to electricity consumption, for which end-users mainly do not pay their value through the cost of the electricity consumption. For example, when an *EV*'s end-user buys such a car he/she pays for the value of transportation, of his/her environmental benefits among others services. In these cases, cost should be treated as sunk costs from an electricity system's perspective, e.g., *EV*s investment cost should be assessed as null and only the energy charged and discharged together with any additional capacity used to provide services to/from the grid should impact adoption. To really assess the adoption of *EV*'s a separate valuation of the services offered by this type of vehicle should be conducted, including, for example, transportation services.

4.1.7 Microgrids as a framework to model economically optimal private decisions to deploy *DERs*, including for example microgeneration, electric vehicles, storage and demand response, showing competition and complementation among technologies.

Distributed Energy Resource (*DER*) is a key term to understand the future of distribution systems, but it is used with dissimilar meanings by different authors in the literature. In this study *DER* is defined as a technology capable of providing electricity services within the distribution system (Pérez-Arriaga & Knittel, 2016). They may include renewable and conventional microgeneration, Electrical Vehicles *EV*, Distributed Energy Storage Systems *DESS* and Demand Response *DR* among other services. These services are normally provided to private users, which are usually also utility's customers, e.g., households, commercial, business or industrial facilities. Volumetric energy tariffs (charging in units of *USD/MWh*) are normally used for smaller customers of utilitys, which tend to be residential loads.

Potential residential *DER* owners have to decide which resources to deploy and which services to buy from the grid. These are private decisions, which take place behind-the-meter, and involve simultaneous optimization of equipment sizes, technology mix and dispatch. Current Literature, so far, only tends to analyze the penetration of particular *DER* technologies into the distribution grid, e.g., *PV*. To model these decisions including all sorts of energy services, local microgrids (μGs) may provide a better framework to technically and economically understand which technologies and services are optimal, which will be preferred by grid customers and how they may compete or complement. Thus, Microgrids allow a deeper understanding of *DER*'s private deployment decision, allowing therefore a deeper insight into Death Spirals (*DS*).

4.1.8 Contribution of this study: A robust worst-case approach to quantify the impact of tariff design on distribution systems, using three different tariff designs and netbilling regulation. Microgrids as a framework for end-users' decision to deploy residential *DER*, including learning curves to estimate future evolution.

In this study we aim to quantify the impact of three different tariff designs on residential end-users, utilities and regulators using microgrid optimization as a robust (worst-case) decision framework for end-user's *DER* deployment. We also estimate the evolution in time of these impacts with scenarios based on the extrapolation of *PV*'s learning curves. The framework is especially suitable for the design of robust regulations that seeks to be fair to utilities and customers when accommodating

DER's penetration into the grid. Some key findings are that both tariff designs and the moment chosen for the new tariff implementation are fundamental for a fair and economically efficient distribution system with massive *DER* penetration.

The most typical tariff designs for residential end-users were chosen including those immune to Death Spiral. Each tariff design has its regulatory pitfalls which may represent economical, societal and political risks for the regulator, utility and end-users. These tariff designs are the following: i) today's volumetric energy tariffs with bundled network and generation costs, ii) today's tariffs but with additional tariff updates due to *DER* penetration and iii) an unbundled two-part tariff that decouples network costs from generation costs. Real Time Markets (*RTM*) are not covered in this study and are left for future studies. A review of *RTM* for the integration of *DER* can be read in (Q. Wang et al., 2015)

The proposed framework for residential end-user decisions extends the analysis usually found in literature for Death Spirals, from a single microgeneration technology (e.g., *PV*) to a more general set of *DERs*. It also extends the analysis from the usual volumetric energy tariff charged to households to any possible tariff design. Finally, it gives a feeling of tariff's time-evolution and impacts on utilities and end-users. The proposed framework reflects the behavior of an economically rational and inelastic end-user, which is the most extreme (worst-case) scenario from a regulatory perspective regarding *DER*'s adoption. Since it is very hard for the current state of the art to forecast *DER* adoption, a robust approach is to assume a simultaneous adoption of all users once a technology becomes feasible (i.e., grid-parity is reached). Of course this framework is only an approximation and reality should evolve slowlier knowing all behavioral biases human beings have. Nevertheless, we think this is a very good starting point and benchmark for future studies.

Chile was chosen as a case study, because it seems to be at its tipping point to reach grid-parity in the distribution system. High radiation and relatively high energy prices has unleashed a race to install *PV* systems without financial aids at the bulk power system. In this study, we use the town of Diego de Almagro as a case study because of its high radiation and because of the government's aims to transform Diego de Almagro into the solar city of the future after a catastrophic flood.

4.1.9 Outline of this study

The remainder of this study is organized as follows: Section 2 describes the main local characteristics of the site and scenarios studied. Section 3 presents the microgrid's and distribution system's developed model. Section 4 describes the dispatch optimization method used. Section 5 develops a model for the capacity-mix optimization. Section 6 presents the main results. Finally, section 7 offers a conclusion to this study.

4.2 Case Study: Scenarios based on *PV* learning curves and three tariff designs for Diego de Almagro in the north of Chile, one of the first places where *DER* could reach grid-parity due to remarkable solar energy resources.

Chile is an excellent country to study the worst-case impact of residential *DER* penetration and on distribution systems due to its outstanding renewable energy resources, expensive distribution charges and net-billing tariff regulation. Global Horizontal Irradiation (*GHI*) is the world's highest in Calama and are in general outstanding in the northern regions as can be seen in Fig. 4-2 (Chile, 2014a; Watts, Valdés, et al., 2015; Woodhouse & Meisen, 2011) (above 2700 $kWh/m^2/yr$ in Calama). This, together with *PV*'s falling costs, puts Chile at its tipping point for a disruptive deployment of residential *DERs*, which could happen without regulatory or financial incentives, just driven by low technology costs.

Chilean net-billing regulation allows electricity end-users of distribution systems to produce their own renewable energy (e.g., solar or wind), selling their surplus generation to the grid, with a maximum capacity of 100*kW*. Thus, end-users have regulated tariffs to retrieve and inject electricity. The advantage of net-billing regulation when compared to net-metering is its better economic efficiency due to net-billing's dissimilar tariffs for the end-user retrieval and injection.

It is very interesting to study net-billing to assess the impact of *DER* penetration on tariffs and stakeholders' costs, because net-billing loosens the symmetry between retrieving and injecting tariffs, offering a broader view of the market's behavior than net-metering. In the Chilean case, which is similar to many other countries, end-users' retrieving tariffs include network charges and generation peak-power costs, while injecting tariffs do not. Thus, retrieving tariffs are usually higher than injecting tariffs. If future price drops of *PV* panels are significant enough, after some cost threshold, end-users could first install *DERs* for self-consumption and only after another significant price decrease they could sell energy to the grid, impacting the distribution and probably transmission systems.

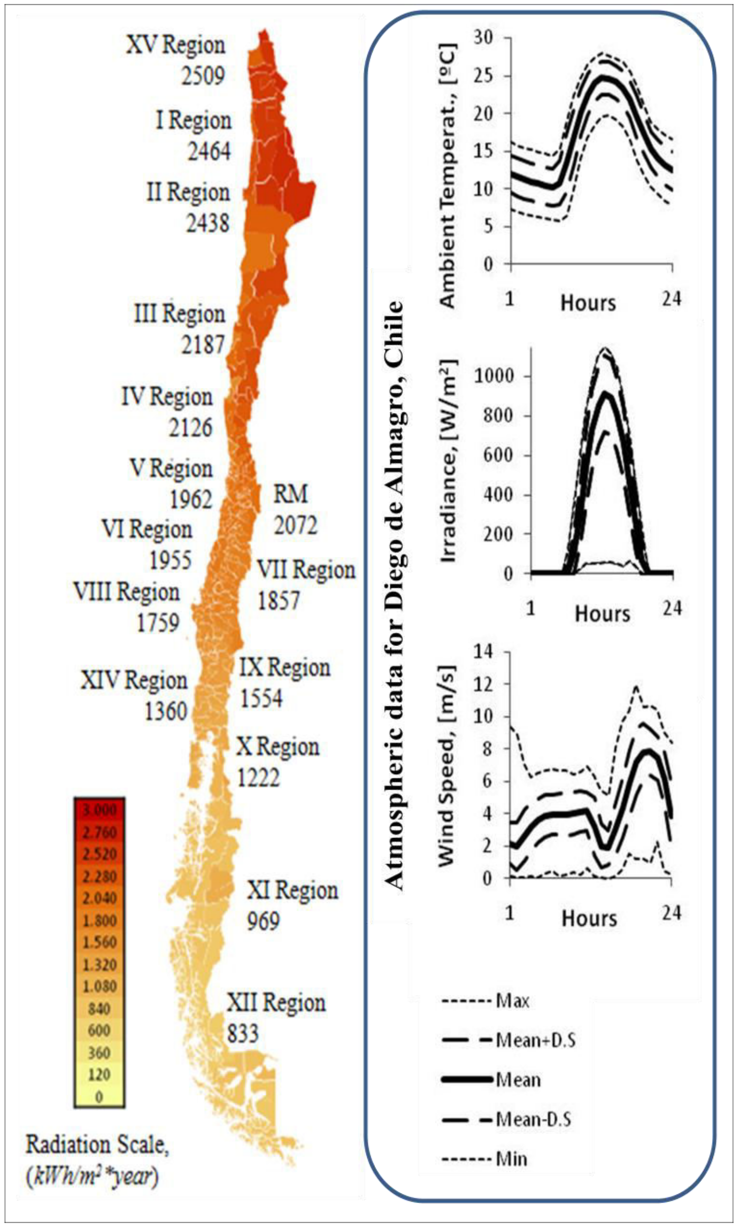


Figure 4-1: Map of Chile colored according to Global Horizontal Radiation (*kWh/m2*year*). Also detailed daily profiles for atmospheric data of Diego de Almagro are given: Temperature (°*C*), Irradiance (*W/m2*) and Wind Speed (*m/s*).

Large-scale deployment of *PV* plants is already happening in the Chilean wholesale power system and in the distribution system by large *DER* before massive household adoption. Large *DER* (3 *MW* – 1 *MW*) and large netbilling *DER* are (100*KW* to 30*KW* and up to 10*kW*) are already being deployed extensively in the north of Chile. Thus, in the last two years this country has seen a boom of *PV* generation competing and undercutting traditional technologies without financial aid. Here *PV* has saturated the main transmission system (*Proyección del costo marginal y comercialización de la energía: desafíos para la minihidro*, 2016) and some northern regions' distribution feeders, demonstrating that grid-parity has been overpassed for large-size generation.

Given this scenario and considering that *PV* costs will continue to fall in the foreseeable future, a large list of other countries will reach grid-parity and will be forced to follow Chilean's lead irretrievably and irreversibly, regardless of their concerns with environmental issues. Thus, Chile could become the first of a large list of countries where grid-parity is reached at the residential level in the distribution system.

To estimate when and to what extend the penetration of residential *DER* is about to change distribution systems in developing countries, we combine the use of several technology price scenarios (*PV* prices and electricity energy tariffs) together with their PV cost learning curves for a particular town in the north of Chile called Diego de Almagro as we explain in this section.

4.2.1 Diego de Almagro: the solar city of the future due to of its excellent solar radiation and reconstruction opportunity.

The government of Chile aims to transform Diego de Almagro into the solar city of the future. This goal comes after it was severely affected in 2015 by a catastrophic flood that destroyed 40% of its households and public infrastructure ("Mayor of Diego de Almagro denounces looting to supermarkets and asks the Government for help," 2016). Our team, together with the Chilean Economic Development Agency (Corfo) ("Strategic program, 'Solar industry'. Technical guide: high-impact strategic public goods for competitiveness," 2016), are part of this initiative, developing a solar city model applicable for the rest of the country considering the low and descending PV costs and the potential of a more resilient distribution system through smart *PV* distributed generation. This initiative seeks to revert Diego de Almagro's catastrophe by both acknowledging its high solar radiation (2424 $kWh/m^2/yr$) (Chile, 2014a) and recognizing the opportunity to rebuild this town.

Today, Diego de Almagro has become one of the mayor hotspot for large-scale *PV* deployment in Chile because of its outstanding radiation and its connection to the main Chilean power system. In the last 2 years, 337 *MW* of *PV* generation have been installed around this small town (*Location of Generators in the Centrally Interconnected System*, 2016) and 215 *MW* are planning to begin their operation before 2020 (*Report of Chilean Project Cadastre*, 2017) mostly to export energy to other regions because demand is much smaller (8.19 *GWh*) ("Electricidad Vendida por Comuna en Segmento Distribución," 2017). This town is located in the north of Chile, 957 *km* from the country's capital Santiago, has around eight thousand inhabitants and has a desert climate with an average radiation of 277 Wh/m^2 including night hours, temperatures between 5.8$°C$ and 28$°C$, and an average air density of 1.111 kg/m^3 (latitude 26° 22' S & longitude 70° 22' W, 923 m.a.s.l.).

4.2.2 Scenarios based on *PV* learning curves and three different tariff designs to assess the end-user decision

For Diego de Almagro three tariff designs were chosen, which are the most traditionally used in distribution systems: i) a today's volumetric energy tariff (Business as usual), ii) today's volumetric energy tariff but with yearly updates due to *DER* penetration and iii) a two-part tariff that decouples network cost from generation.

The evolution in time of all three tariff designs were assessed with scenarios base on world's *PV* learning curves. This was done by extrapolating world's *PV* learning rate and exponential production growth, resulting in an expected *PV* panel cost-reduction of 8% per year. The learning rate obtained was 21%, calculated from *PV* panel's prices from 1977 to 2015 and in line with the literature. The world's *PV* panel production trend was obtained from adjusting an exponential curve to the cumulative capacity of *PV* panels manufactured between years 1977 and 2015. Both production and price trends can be seen in Fig. 4-3. For these trends a time-horizon of 10 years was used once any *DER* technology becomes economically viable starting with today's tariff and costs conditions.

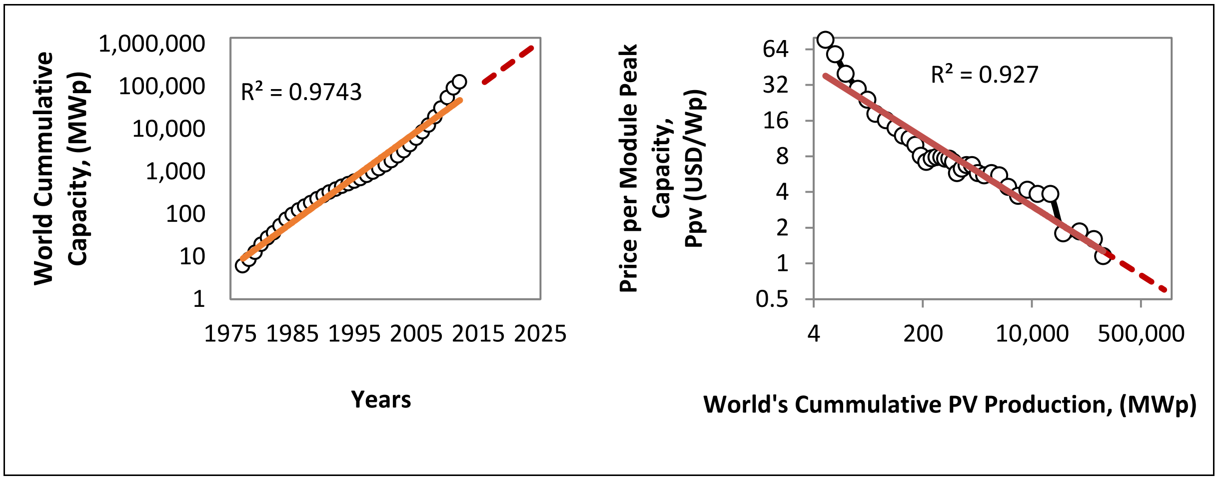


Figure 4-2: Impressive cost reduction of renewable energies and batteries for period 2008-2015. A) World's cumulative capacity manufactured. B) *PV* panel's price per module's peak capacity in logarithmic scale

In the special case of a volumetric energy tariff with yearly tariff update due to *DER* penetration, tariff was iteratively calculated until convergence was obtained. This is, the following steps were repeated iteratively until the tariff increase and the resulting *DER* installation of the end-user converged: i) end-users' reevaluation of the optimal local microgrid due to the tariff update was calculated and then ii) a new tariff-update was obtained from the reevaluation. Finally, a sensitivity analysis was conducted for a range of values of the variables i) *PV* panel cost and ii) utility's selling tariff to the customer. In total 70 scenarios were calculated, allowing us to demonstrate the evolution in time of the three tariff designs within a broader perspective. These 70 scenarios allow also understanding the dominant (and omitted) technologies (Diesel generator, gas turbine, battery bank, *PV* system and wind turbine) under each *PV* cost and tariff combinations.

4.2.3 A typical mean Chilean load profile

A daily average residential load profile for a Chilean urban area supplied through a distribution system was chosen for this study. The characteristics of such a load profile are: i) no air conditioning consumption (*A/C* is rare in *LATAM*), ii) a peak load consumption at the late evening hours (because people are home using lighting, *TV*, etc.), iii) a lower flat consumption during sun hours (since less people are home, lighting is in general not needed and activities are more uncorrelated, e.g., washing machine, iron, radio, computer, microwave oven.) and iv) decreasing consumption during the late night and early morning hours (because people are sleeping at home) reaching its minimum around dawn. This reference load profile can be seen in Figure 4-3.

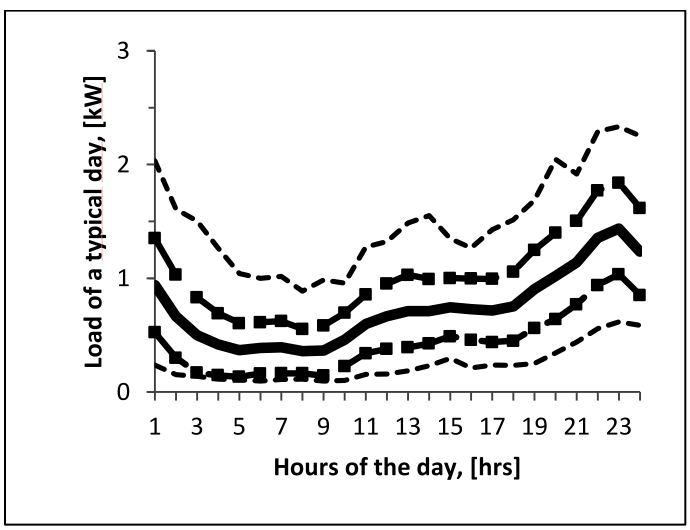


Figure 4-3: Load Profile used for Diego de Almagro. Average residential load profile for a Chilean urban area supplied through a distribution system. Mean load

(very thick and continuous line); one standard deviation from the mean (thick dashed line); Max/min loads (thin dashed line).

4.3 Microgrid and Distribution system models

In the last years, a global trend is changing distribution systems by transforming end-users' role from the traditional electricity consumer into a proactive one that can additionally act as a local microgenerator or storage system either for its self-consumption or to inject energy into the grid. This new end-user behavior can be modeled as a local optimized microgrid because these small power systems have the flexibility to integrate a whole range of technologies and services. For example, microgrids may include all possible generation, storage and demand response technologies or services. Nevertheless, distribution systems should be adapted to the new operational condition of a bidirectional grid in order to maintain quality of service, which can be achieved through reconfiguration (Baran & Wu, 1989; Cao, Wu, Jenkins, Wang, & Green, 2016) or *DER* integration (Hung, Mithulananthan, & Bansal, 2014). Also, this adaptation may improve demand and generation hosting capacity (Thomas, Burchill, Rogers, Guest, & Jenkins, 2016).

In this section, we show how we model the distribution system, the microgrid, each individual *DER* and their interaction.

4.3.1 Microgrid definition

Microgrids are small-scale independent electrical power systems that may aggregate different combinations of distributed energy resources *DER*, electric vehicles (*EV's)*, distributed energy storage systems *DESS* or demand response *DR* together with thermal and electrical consumptions. They can be designed as isolated systems or connected to the macrogrid. If connected to the macrogrid they can be operated in parallel or islanded from the main electrical grid (C Bustos et al., 2012; Hatziargyriou, Asano, Iravani, & Marnay, 2007; Lasseter, 2002; Lasseter & Paigi, 2004; Faisal A Mohamed & Koivo, 2010). Even more, microgrid may enhance distribution system resilience by sectionalizing the grid into self-supplied subsystems (Lu, Wang, & Guo, 2016; Z. Wang & Wang, 2015).

4.3.2 Microgrid control, configuration and technologies

Local voltage and frequency controls for each *DER* are allowed by power electronics and local instrumentation (Olivares et al., 2014) (Lasseter & Piagi, 2006). To optimize its operation economically the Energy Manager (*EM*) performs the dispatch of each *DER* with the main grid (Olivares et al., 2014), adjusting the setpoints of the local controls. The connection to the macrogrid is called Point of Common Coupling or *PCC* and from here the μG is usually built as a radial system with feeders that can be dedicated to different reliability needs such as critical loads (backuped by dispatchable *DERs*), controllable loads (like *HVAC* with temperature setpoint) and sheddable loads. Such an example is represented in Fig. 4-5. In this study we assume only critical loads with all *DERs* connected to the same feeder.

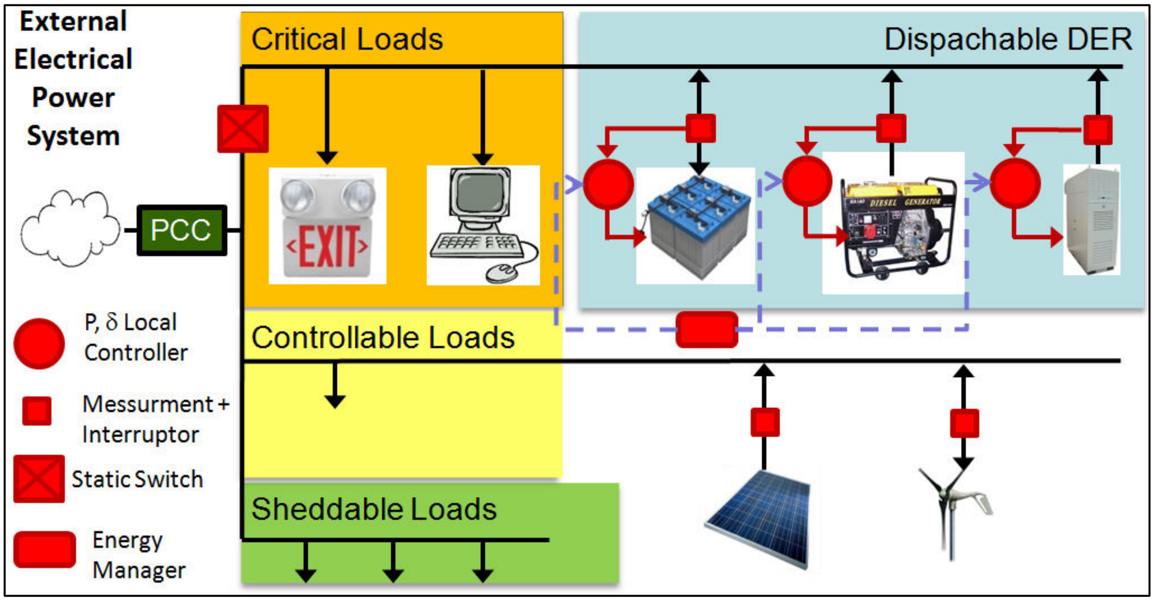


Figure 4-4: Microgrid's typical Architecture. It may contain critical loads which should be backuped controllable loads which could have loads and *DER* (but are not backuped) and a sheddable loads which are usually only loads. In this study we assume only critical load.

In this study, microgrids are composed of electrical *DER*s, which in turn can be separated into microgeneration and *EV*. Each generation technology typically used in a microgrid is modeled: i) small wind turbines, ii) photovoltaic solar panels, iii) diesel generators and iv) gas micro-turbines. In turn, *EV*s are modeled as lithium ion batteries (i.e., storage). Each generation technology is modeled based on the paper presented by Bustos and Watts (Cristian Bustos & Watts, 2017). Nevertheless, in this study *EVs* and a grid-tied microgrid were considered for the end-users bill minimization. The model for each *EV*, for the distribution system and its interaction to the microgrid are explained next.

4.3.3 Electric Vehicle

Electrical Vehicles (*EV*) are seen as batteries from the grid's perspective. They have to be charged but may provide both tariff arbitrage (between high and low tariffs) and ancillary services (for the power system, such as spinning reserve and frequency regulation). These services are known as Vehicle-to-Grid or *V2G* and should make economically sense when its primary service is the transportation service, i.e. when *EV*'s investment costs become mainly sunk cost for *V2G*, Thus, in this study only additional storage capacity is treated as an investment cost for *V2G*'s services (Kempton & Tomić, 2005a, 2005b). It has to be noted that ancillary services are not analyzed in this study because the inertia of small scale *DER* would need much faster time resolution than the ones considered here, reaching as low as minutes or even seconds.

The mainstream technology for *EVs* are Lithium-ion batteries (Li-ion) which have a better performance than lead acid (better efficiency), comply with space restrictions in *EVs* (higher energy density, higher power density), but have a higher price per unit of energy than lead-acid. Li-ion batteries are modeled as a lineal energy storage balance (energy flowing into the battery system minus the energy flowing out has to be equal to the change).

Each battery has a maximum normalized charge and discharge current ($I_{EV,max}$), a nominal voltage $V_{EV,r}$, a charging efficiency $\eta_{EV,c}$ when it is charged with a power $P_{EV,c}$, and a discharging efficiency $\eta_{EV,d}$ when it is discharged with a power $P_{EV,d}$.

Li-ion batteries for EVs possess an upper State of Charge (*SOC*) limit $SOC_{EV,max}$, a lower *SOC* limit $SOC_{EV,min}$ and an initial State of Charge $SOC_{EV,ini}$. The model equations of the battery bank are:

$$P_{EV,d} = (I_{\mathrm{EV,d}} V_{\mathrm{EV,r}} U_{EV} N_{EV})/\Delta t \tag{4.1}$$

$$P_{EV,c} = (I_{\mathrm{EV,c}} V_{\mathrm{EV,r}} U_{EV} N_{EV})/\Delta t \tag{4.2}$$

$$SOC_t = SOC_{t-\Delta t} - (\eta_{\mathrm{EV,c}} P_{EV,c} + \frac{1}{\eta_{\mathrm{EV,d}}} P_{EV,d}) N_{BAT} \tag{4.3}$$

$$SOC_{min} \le SOC_t \le SOC_{max}, \tag{4.4}$$

where Δt is the time between measurements and t is the time of each measurement, $I_{EV,d}$ is the per unit discharge current, $I_{EV,c}$ is the per unit charge current, $V_{EV,r}$ is the nominal system voltage, *UEV* is the battery capacity in *Ah*, $\eta_{EV,c} = 0.85$ is the charging efficiency and η_{BAT_d} is the discharging efficiency (which we considered equal).

Electric vehicle's battery parameters used are $V_{EV,r} = 24V$, $U_{EV} = 125Ah$, $\Delta t = 1hr.$, $0 \le I_{\mathrm{EV,c}} \le I_{EV,max} = 0.67$ $0 \le I_{EV,d} \le I_{EV,max}$, $SOC_{EV,ini} = 0.5SOC_{EV,max}$ and $SOC_{EV,min} = 0.5SOC_{EVmax}$. Note that N_{EV} represents the number of batteries used by all *EVs* and is determined by the capacity optimization.

4.3.4 Distribution system cost, tariffs and end-user connection

In general, Chilean residential distribution system's end-users connected to the grid pay a monthly bill for their electricity consumption that is composed of i) a fixed charge equal for all users (*USD/client/month*), ii) a unique charge for the use of the main transmission system that is paid per unit of energy (*USD/MWh*) and iii) a charge per unit of energy that bundles network-, generation- and policy costs into one volumetric tariff (*USD/MWh*)[20]. Although there are other tariff designs, this is the one most typically used by households. This tariff is called *BT1*; it considers low voltage supply and is defined by the following formulas:

$$C_{EG} = CFES + (CU + BT1) \cdot E_{EP} \tag{4.5}$$

$$BT1 = BT1_E + BT1_P + BT1_{Dx} \tag{4.6}$$

$$BT1_{Dx} = (CBDT \cdot CDBT_{index})/NHUDB \tag{4.7}$$

where C_{EG} is the total cost of the electricity purchased from the grid, *CFES* is a fixed charge per end-user and is 1.7629 *USD/month*, *CU* is the cost of transporting energy through the main transmission system and is 2.2477 *USD/MWh*, $\mathrm{E_{EP}}$ is the electricity purchased from the grid (*MWh*), *BT1* is the bundled tariff that includes the network tariff and the generation costs, $BT1_E$=94.22 *USD/MWh* is the cost of the energy consumed by the end-user, $BT1_{Dx}$ is the network tariff charged per unit of energy, $CBDT$=11976 *USD/MWh* is the distribution network cost of year 2013, $CBDT_{Index}$ is the index that adjusts *CDBT* each year and starts at a factor of one in 2013 and *NHUDB*=450 are the peak load hours. According to this it is possible to calculate $BT1_P$.

[20] Recently, some policy costs have been added in Chile to the residential energy tariff with both income-related redistributal objectives and to compensate households in areas where electricity generation has been installed massively. These costs are not considered in this study because the regulation that defines them came into force just after the data for this study was collected.

Utility's distribution system income is updated if a Death Spiral develops and increases tariffs. This is, each time more residential *DER* penetrates the system, less energy is purchased from the grid and thus P_{EP} decreases, which in turn increases $BT1_{Dx}$ in order to keep utility's distribution system income constant. The equation that relates income to tariff and energy purchased is the following

$$I_U = BT1_{Dx} \cdot E_{EP} \tag{4.8}$$

The bill paid by each household depends if he/she is a *DER*-owner or not. For a non-*DER*-owner his/her bill C_{NonDER} only has to pay the electricity purchased from the grid and its related costs according to *BT1* tariff design.

$$C_{NonDER} = CFES + (CU + BT1) \cdot E_{EP} \tag{4.9}$$

For a household that is also a *DER*-owner he/she has to pay an annuity $A_{\mu G}$ that is related to the present value $NPV_{\mu G}$ of the investment in an optimized local microgrid plus the bill to the utility at a discount rate *r* and an evaluation horizon *h*. To obtain a monthly payment for the microgrid annuity can be divided into 12 equal payments, one for each month of the year.

$$A_{\mu G} = \frac{NPV_{\mu G}}{\left[\frac{1}{r} - \frac{1}{r \cdot (1+r)^h}\right]} \tag{4.10}$$

For a *DER*-owner its bill C_{DER} is a bit more complex. In addition to the annuity related to the microgrid and the electricity bill paid to the utility due to purchased electricity, *DER*-owners have the benefit of selling energy to the grid, receiving an income from the utility. This income will be discounted from the bill end-users have usually payed to utilities so far. Thus, the final formula for the cost of *DER*-owners is the following.

$$C_{DER} = CFES + (CU + BT1) \cdot E_{EP} - I_{ES} \cdot E_{ES} + \frac{A_{\mu}G}{12} \tag{4.11}$$

We assume that the solar penetration at the microgrid level does not affect the total amount of capacity required for adequacy, especially not the capacity purchased from the grid. This makes sense because of the importance of *PV* generation in such a sunny place as Diego de Almagro, whose peak generation hours at mid-day do not match evening's peak- load hours.

4.4 Dispatch optimization: Mixed Integer Linear Programming considering load and renewable generation

In this study microgrid's operation is economically optimized in 2 steps as shown in Fig. 4-6: i) first, *PV* and wind Distributed Energy Resources (*DERs*) are dispatched due to their zero marginal costs in Node 2 (4.13) and ii) then the remaining net load $P_{NET\ LOAD}$ is supplied by dispatching all the different conventional *DERs* and Electric Vehicles (represented by Li-Ion batteries) efficiently in Node 1. This optimization includes the capability of disconnecting conventional generation (diesel and gas) (4.14), usually known as the unit commitment (*UC*) problem. Contrary to the criteria used in the proposed methodology, which is based on a worst-case scenario that allows a robust regulation, for the dispatch of *DERs* the expected values for the net-load and the renewable generation were used. This is based on the fact that different worst-case scenarios can be found for maximum penetrations of conventional and renewable generation.

To avoid any bias in favor of a specific *DER* technology, taking into account the variability of load and renewable resources and including the capability of disconnecting conventional generation a deterministic method was used based on Stochastic Programming (*SP*). This method was solved using a deterministic equivalent based on Mixed Linear Programming (*MILP*) taking into account the expected value for the load and the renewable generation (i.e., solar and wind). SP has been used in other studies to cope with renewable resources' and load variability (Niknam et al., 2012) and is known to be one of the most powerful optimization tools available. Other interesting methods are robust optimization (*RO*), which reduces some tractability issues as recognized by Velasquez (Velasquez et al., 2016) and Chance Constrained Stochastic Programming, which assigns a probability to a restriction (Moarefdoost, Lamadrid, & Zuluaga, 2016).

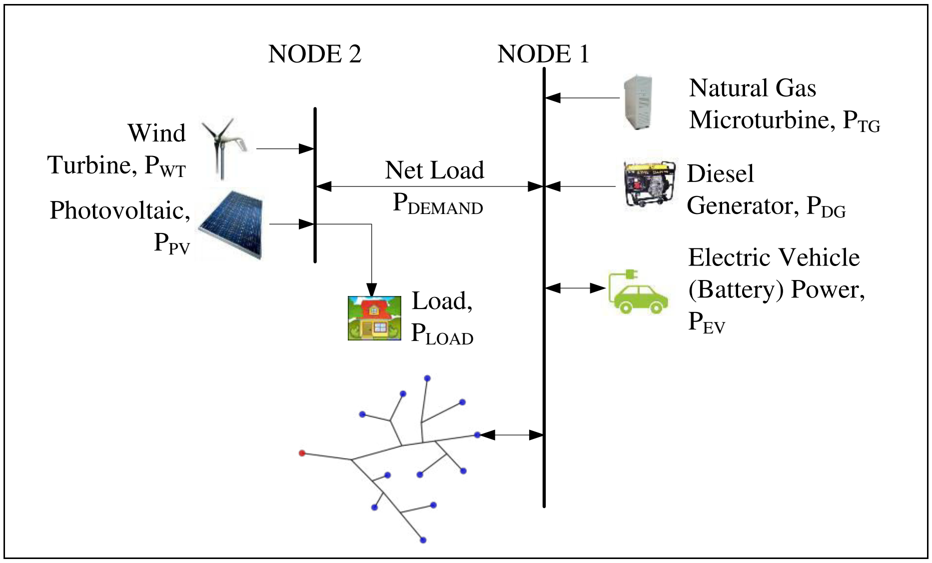


Figure 4-5: Diagram of optimized local microgrid connected to the grid. Firstly renewable energies are dispatched (Node 2) and then the conventional generation is optimized over the resulting net demand (Node 1). Power flows entering Node 1 are positive.

According to the original concept of Lasseter (Lasseter, 2002) each local microgrid's *DER* has power electronics, which allows local control frequency and voltage through the management of active and reactive power in order to stabilize the system without a centralized algorithm. Since loads are assumed to be in the end-user's dwelling distribution lines are pretty short and thus line losses are negligible.

4.4.1 Objective Function: minimization of fuel costs and cost of energy not supplied

The optimization is performed by minimizing the sum of all *DER*'s fuel consumptions, the cost of energy purchased from the grid and the income of the energy sold to the grid for each time t. Thus, the objective function is the total dispatch cost *DCost*:

$$DCost = \sum_t (C_{DG}P_{DG} + C_{TG}P_{TG} + C_{EP}P_{EP} - I_{ES}P_{ES}) \cdot \Delta t \qquad (4.12)$$

Where Δt is the time period, C_{DG} is the fuel cost of one unit of generated power for the diesel generator, P_{DG} is the power generated by the diesel generator, C_{TG} is the fuel cost of one unit of generated power for the gas microturbine, P_{TG} is the power generated by the gas microturbine, C_{EP} is the cost of purchasing one unit of electricity from the grid, P_{EP} is the electric power purchased from the grid, I_{ES} is the income of one unit of electricity sold to the grid and P_{ES} is the electric power sold to the grid.

4.4.2 Restrictions: *DER*, *EV* and system restrictions are included in the model

Operational Restrictions can be classified into *DER* restrictions, Electrical Vehicle (*EV*) restrictions and system restrictions. *DER* restrictions correspond to i) minimum and maximum generation limits, ii) in-operation or shut-down status of conventional generation and iii) *PV* and Wind turbine production models. *EV* restrictions refer to restrictions related to Li-ion batteries, thus i) battery charging limit, ii) battery discharging limit and iii) energy balance. The details of these restrictions and models are described in Subsection *4.3: Microgrid and distribution system models* and are as follows:

System restrictions are related to the power flow balance between all *DERs* in the system and loads. In this sytdy we first dispatch renewables. To supply the remaining net load $P_{NET\ LOAD}$ conventional generation and *EV*'s batteries are balanced together with $P_{NETLOAD}$. This is shown in the next equations:

Net Load: *PV* and wind generation has to be subtracted to the total load because they are dispatched at zero marginal cost.

$$P_{NET\ LOAD} = P_{LOAD} - P_{WT} - P_{PV} \tag{4.13}$$

Balance of Power: The sum of the power supplied by each *DER* or *EV*'s batteries, stored, retreived from grid and injected to the grid should be equal to the Net Load.

$$P_{NETLOAD} = P_{DG} + P_{TG} + P_{EV,d} + P_{EV,c} + P_{EP} + P_{ES} \tag{4.14}$$

P_{LOAD} is the total power of the load, P_{WT} is the power generated by the wind turbines, P_{PV} is the power generated by the PV panels, $P_{EV,d}$ is the power discharged from *EV*'s battery system, $P_{EV,c}$ is the power charged into the *EV*'s battery system P_{EP} is the power retreived (i.e., purchased) from the grid and P_{ES} is the power injected (i.e., sold) into the grid. We assume without loss of generality that all power injected into the load is positive, thus P_{EP} must be positive ($P_{EP} > 0$) and P_{ES} must be negative ($P_{ES} < 0$).

4.4.3 Diesel and gas fuel costs in Chile

Public information and tax schemes were used to estimate diesel and natural gas costs. Diesel was assumed to have a public selling price of 430 *CH$/ltr* according to National Energy Commission's average information for the 3rd Region of Chile. Gas was assumed to have a public selling price of 408 $CH\$/m^3$ @ STC, also according to the National Energy Commission. These prices correspond to December 2016

For the estimation of the diesel and natural gas fuel costs, public information and tax schemes are used. For diesel the mean public selling price of 430 *CH$/ltr*. (Chilean pesos per liter) for the 3rd Region of Chile registered by the National Energy commission of Chile is used (*Precios observados a Público: Promedios nominales en regiones y Región Metropolitana (Precio Diesel, Octubre)*, 2015). Additionally, an exchange rate of 658 *USD/CH$*, *UTM* of 46229 *CH$* and a *VAT* of 19% was used (*VAT* was included in all prices).

4.5 Capacity-mix Optimization

In this study, a local microgrid (μG) is used as a framework to minimize costs of an end-user who has to decide if he/she will install *DERs* or not. The μG is designed by optimizing the technology mix of the μG using a Genetic Algorithm (*GA*), where the most widely used *DER* technologies are considered.

4.5.1 Optimization of the capacities of the technology-mix using Genetic Algorithms

To optimize the technology mix of the μG, a Genetic Algorithm (*GA*) was used because of the highly non-linear and discrete nature of the dispatch problem and due to the need to explore capacity-mixes in a continues solution space (because the sensibility of the tariff and of the distribution system's stakeholders is not known a priori). Its objective function is the total cost of the end-user. *DER* technologies considered in this optimization are the following: diesel generators, wind turbines, photovoltaic panels and electric vehicles.

In general, interactions between wholesale energy markets and retail markets have to be considered, especially in places where solar generation is important. It is well documented that a large penetration of solar generation will drop wholesale prices at solar production hours, which will in turn stop rational agents from investing further in solar projects (Schmalensee, 2015). Nevertheless, such an ideal relation between wholesale and retail market does not exist in Chile. In fact, those markets are fairly decoupled due to centralized bidding mechanisms put in place, which transform into *PPAs* contracts signed some years in advance of the actual energy supply and for time periods that surpass a decade (law 20.805 of the year 2015). Besides decoupled markets due to centralized bidding mechanisms, other pools of contracts exist (e.g., due to other bidding processes), which makes the influence of each bidding even more insensible to the end-user. Thus, in our study we consider the retail market of the distribution system under *DER* penetration as independent of the wholesale market.

The optimization variables of the technology mix represent the nominal installed capacity of each type of *DER*. These are the following: Wind turbines rated power $P_{WT,r}$; Photovoltaic System rated power $P_{PV,r}$; Diesel Generator rated power $P_{DG,r}$; gas turbogenerator rated power $P_{TGG,r}$; total capacity of the Electric Vehicle's Battery Bank U_{EV} and Battery Charger rated power $P_{EV,r}$. All these variables must be greater than zero and smaller than a certain maximum value $\vec{P}_{nom_{max}}$

4.5.2 Assumptions and costs used in the calculation of the end-user's total microgrid cost.

In order to size the optimal technology mix, the operational costs obtained in the optimization of the dispatch are used as input together with the *O&M* cost. For the calculation of total cost of the μG the following assumptions are used to represent the "average" cost of a project in Chile:

- Fuel costs, electricity cost of purchasing from the grid and selling to the grid: Calculated by the optimal dispatch,
- Capital costs of each *DER* (Table 4-1),
- Replacement costs of each *DER* (Table 4-1),
- Operation and Maintenance (*O&M*) costs ex-fuel of each *DER* and *EV* (Table 4-1),
- Lifetime of each *DER* and *EV* (Table 4-1),
- Discount rate of 10% (Watts, Albornoz, et al., 2015),
- Microgrid expected lifetime: Evaluation horizon of 20 years,
- Contingencies and Balance of Plant (*BOP*) costs: added on top of investment costs (10%).

- Project management, project development and logistics costs: added on top of investment costs (10%).
- Inland transportation costs: These are almost negligible (around *USD* 100 for the whole system) because the community is relatively near to a possible Chilean harbor (150 *km* from the harbor of Caldera) with a good access route.

Table 4-1: Costs and Life Time of Technology Mix

DER Type	**Refe-rence**	**Investment Costs**			**Annual O&M Cost (non-fuel)**[21]		**Life-time**
		Unit	**Capi-tal**	**Reposi-tion**	**Unit**	**Value**	**[years]**
Diesel generator	a	USD/ kW	900	756	USD/ kWh	0.014	4
Gas turbine	a	USD/ kW	1500	900	USD/ kWh	0.010	2
EV's Battery Bank	b	USD/ Wh	250	192	USD/ kWh	13	5
Wind Turbine	c	USD/ kW	6260	N/A	USD/ kW	90	20
PV Panel	d	USD/ kW	2000	N/A	USD/ kW	20	25

[a] (*A Review of Distributed Energy Resources. New York Independent Operator*, 2014)
[b] (M. Arriaga et al., 2013; Matteson & Williams, 2015; York, 2014)
[c] (Orell & Foster, 2015)
[d] (*A Review of Distributed Energy Resources. New York Independent Operator*, 2014; Watts, Valdés, et al., 2015)

[21] No se incluye el costo de combustible, que se trata separado en la sección *4.4.3. Diesel and gas fuel costs in Chile*

4.6 Results

Results presented in this section show the most extreme (worst-case) impact that residential *DER* penetration could cause on utility's income and customer's average costs, i.e. when al end-users deploy *DER* at the same time. A site with an outstanding solar radiation was studied, located in the north of Chile called Diego de Almagro. Not surprisingly, results show that in the foreseeable future *DER's* dominant and only technology will probably be *PV* and its deployment would begin in 1 or 2 years if cost of *PV* panels continues to fall at a rate of 8% per year and regulation remains the same. Nevertheless, *PV* adoption could be delayed even further due to other complementary variables - besides grid-parity - such as hidden costs, environmental concerns, social networks and adopter categories, which were not analyzed here.

Three tariff designs were studied considering Chilean netbilling regulation: i) today's volumetric energy tariff sold by the utility to the end-user from the grid, which includes generation, transmission and distribution in one value, ii) today's volumetric tariffs but updated yearly to secure utility's profit and iii) a two-part tariff with network costs decoupled from energy costs.

Results show that rooftop residential *PV* penetration into Diego de Almagro's distribution system will follow in two time-periods. When considering current volumetric energy tariffs, with or without tariff updates, *PV* panels will first reach grid-parity with netbilling's retrieving energy tariff. After around 4 years, *PV* panel costs should fall below grid-parity of netbilling's injecting energy tariff. During the first period, the savings for end-user to install *PV* will be only marginal compared to the alternative of not installing them (in average 3.34% for this period). Nevertheless, in the next 5 or more years, the difference in cost between both end-users becomes colossal, reaching 137% in 2028. When considering a two-part tariff that decouples the network-cost from the energy-cost (where its retrieving energy tariff is equal to its injecting price), *PV* will not be deployed for the first time-period. Only after that (and similar to the second time-period of both other tariff designs) the difference in cost between end-users that would install *DER* and others who would not could become overwhelming.

For today's tariff design, during both periods, utilities could face significant bankruptcy risk due to 30.49% less income during the first 4 years and 47.04% for the next years until 2028. This risk is especially critical when considering that Chilean regulation, allows utilities to earn around 10% of profit. This suggests that a redesign of tariffs is mandatory.

If today's tariffs were updated to secure utility's profit, a Death Spiral (*DS*) effect could develop which would raise tariffs and *DER* deployment would be cross-subsidized by the utility. Conversely, a two-part tariff that decouples network-costs from energy generation costs could secure utility's profit and avoid a *DS* but could create problems for some end-users. In order to have a sensibility of the impact *DER* penetration could have under all three tariff designs, 70 scenarios were selected with a range of *PV* panel costs and of electricity volumetric tariffs offered by the utility to households. For each scenario the optimal microgrid was calculated in two stages: i) the capacity technology mix using Genetic Algorithms (*GA*) and ii) the economical dispatch using Mixed Integer Linear Programming (*MILP*). Additionally, the evolution of costs for utility and end-users was calculated considering the PV panel price evolution expected.

To assess the most extreme (worst-case) impact residential *DER* penetration could have on utility's income and customer's costs some assumptions were made: i) all consumers are equal (average end-user), ii) all customers are economically rational (Any *DER* will be deployed if its grid-parity is reached and end-users will optimize costs), iii) network cost remains constant and iv) system losses are irrelevant. Also, as a framework to understand the decision of households to deploy *DERs*, the technology mix and operation of a local microgrid is optimized.

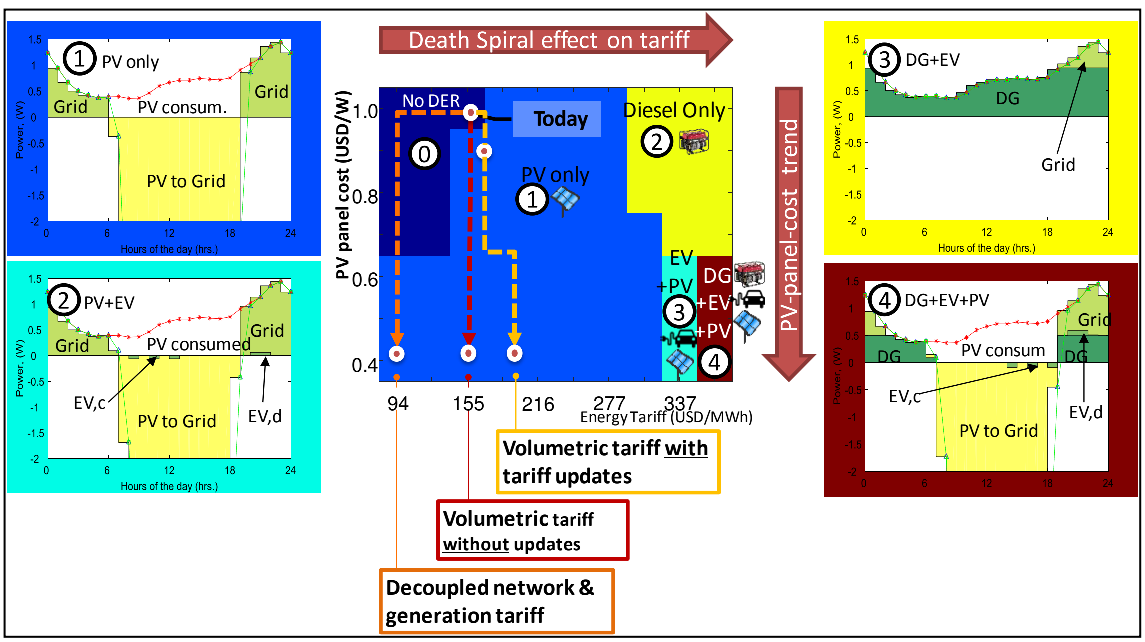


Figure 4-6: Map of 70 scenarios and 3 tariff design paths for the case of Diego de Almagro. Five different technology mix types are identified and their dispatches are shown: 0) Unfeasible µG; 1) *PV* only; 2) Diesel only; 3) Diesel+*PV*; 4) Diesel + *EV* + *PV*. Scenarios chosen cover *PV*-costs in intervals of 100 *USD/W* and utility's tariff

scenarios in intervals of 30 *USD /MWh* (20 *pesos/MWh*). Tariff designs are: Decoupled network & generation tariff (orange to the left), volumetric tariff without updates despite of death spiral (red in the center) and volumetric tariff with updates due to Death Spiral (yellow to the right)

4.6.1 *PV* could become the dominant *DER* technology in Diego de Almagro.

Not surprisingly, results show that in the foreseeable future Diego de Almagro's dominant and only *DER* technology would probably be *PV* according to 70 scenarios calculated for different PV panel costs and volumetric energy tariffs as shown in Fig. 4-7. Its deployment would begin in 1 or 2 years (we assume in 2019) if cost of *PV* panels continues to fall at a rate of 8% per year from today's 1000 *USD/MWh* to 900 *USD/MWh*. This rate is based on both i) the exponential growth of PV panel production worldwide as seen between the years 1977 and 2012 and ii) the industry's learning rate of 21% for the same period of time, which has reduced *PV*-costs impressively.

Nevertheless, if tariff would be redesigned into a two-part tariff that decouples network and energy costs, secures utility's income and avoids price-instability of the Death Spiral, *PV* deployment would be delayed around 4 years, probably just beginning in 2023, which would be an unpopular decision if *PV* deployment is demanded by society. *PV* adoption could be delayed even further due to other complementary variables - besides grid-parity - such as hidden costs, environmental concerns, social networks and adopter categories, which were not analyzed here.

4.6.2 Two step residential *PV* penetration: i) self-consumption during the first four years, ii) injection into the grid the next years.

Residential *PV* penetration into Diego de Almagro's distribution system will follow in two time-periods, according to simulations obtained, depending of the relationship between retrieving tariffs and injecting tariffs. For today's tariff design with or without updates, a *PV* panel cost of 0.9 *USD/W* will pass below grid-parity with netbilling's retrieving energy tariff, incentivizing *PV* installation for self-consumption for the following 4 years (between 2019-2022). This happens only because retrieving tariffs are higher than injecting tariffs for netbilling, which is not the case using a two-part design. That is, with a two-part tariff that decouples the cost of the network from the cost of energy generation, *PV* will not be deployed during the first 4 years, because it cannot be financed by low cost of energy alone (in this case 94.22 *USD/MWh*). After those first 4 years (probably in 2023) *PV* panel's costs should fall even further, below 0.65 *USD/W*, to reach grid-parity of netbilling's injecting energy tariff (the same 94.22 *USD/MWh* in the case of the two-part tariff), incentivizing the deployment of PV energy generation to be sold to the grid in all three tariff designs studied. This two time-periods are shown for today's tariff design with and without updates in Fig. 4-8. Of course *PV* adoption could be delayed even further due to other complementary variables - besides grid-parity - such as hidden costs, environmental concerns, social networks and adopter categories, which were not analyzed here. This adoption delay is not known and very hard to predict accurately.

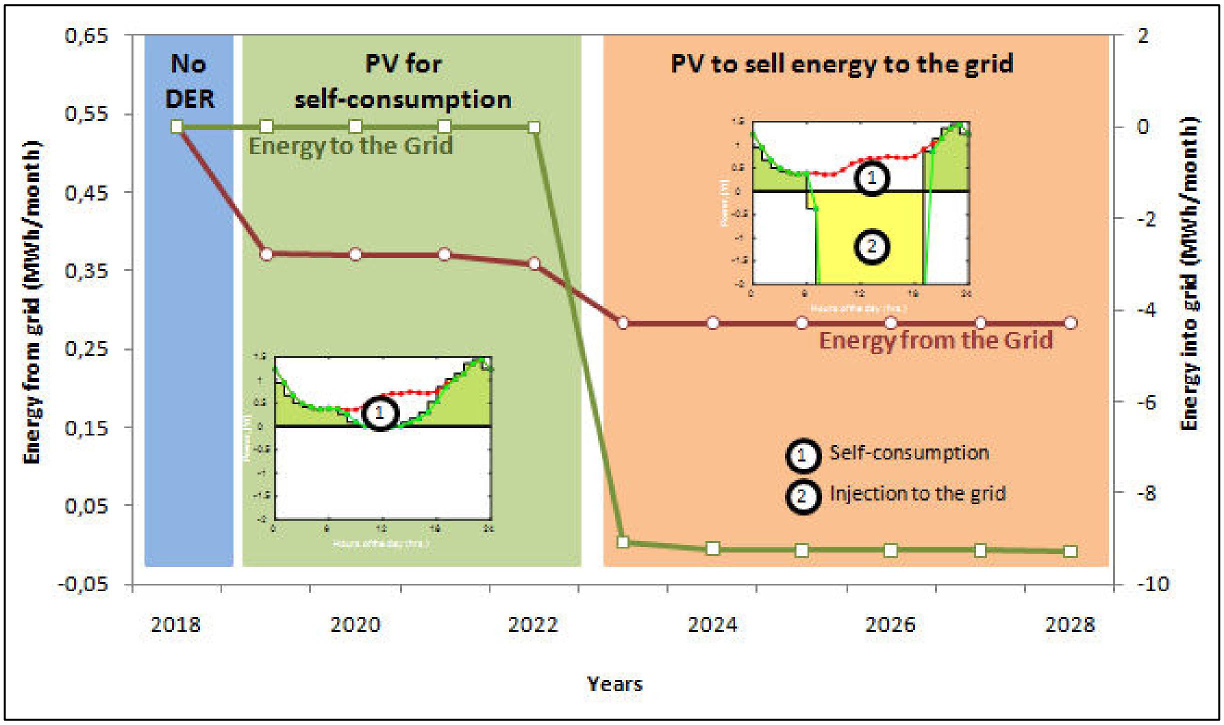


Figure 4-7: Will distribution system survive *DER*? Results show there is life after *DER* in Diego de Almagro. If volumetric tariff are kept bundled (with or without tariff update). During the first time-period end-users will install rooftop *PV* to satisfy self-consumption (2019 – 2022). After that *PV* becomes cheap enough to sell energy to the grid (2023 – 2028). Rooftop *PV* will inject energy into the grid during the midday hours and the grid will supply the end-user during the rest of the day.

4.6.3 Savings of end-users installing *PV* could become on average only 3.34% until 2022. Then, end-users' savings could become massive increasing linearly until 2028, up to a difference of 137%, between *DER* owners and non-*DER* owner.

During the first 4 years the savings for residential end-user to install *PV* will be only marginal compared to the alternative of not installing (in average 3.34% for this period). Nevertheless, at least in the next 6 years, difference in cost between both end-users could become colossal, increasing linearly until they reach 137% in 2028 as shown in Fig. 4-9.

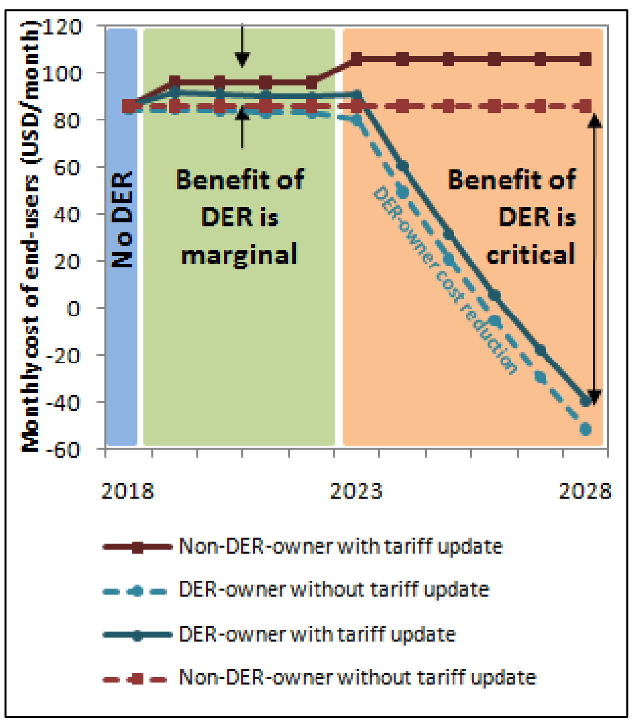


Figure 4-8: Monthly cost of end-users in Diego de Almagro. Cost difference between *DER*-owners and non-*DER*-owners becomes critical in the second time-period

when PV injects energy to the grid. During the first time-period cost difference is marginal.

The penetration of *DER* in two time-periods will be very similar whether the tariff is left as usual or updated (producing a Death Spiral). This means that the Death Spiral seems to have no real impact on the decision to install *DER*, which is counterintuitive and is explained by the discrete nature of a rational investment decision. *DER* is installed when grid-parity is reached. Nevertheless, although a decoupling two-part tariff theoretically eliminates the possibility of *PV* deployment for self-consumption, its effect is only marginal in costs for end-users compared to the other tariff designs.

4.6.4 Non-*PV* technology mixes are possible only at very high network tariffs. Total cost of the optimal microgrid decreases with falling *PV* panel costs and lower network tariffs.

In total, 70 scenarios were selected to conduct a sensitivity analysis, varying the *PV* panel cost and the volumetric tariff for Diego de Almagro, which gives a comprehensive overview of *DER* penetration. For this analysis, *PV* panel cost was chosen as a variable because it is the major market trend today for small-scale applications. Also, tariffs were chosen as a variable to better understand Death Spiral and tariff decoupling effects. As a framework to assess an end-user's decision to install *DER*, local optimal μGs were used. Possible technology options considered are: *PV* systems, small-scale wind turbines, gas microturbines, diesel generators and electrical vehicles. The scenarios chosen cover *PV*-costs ranging from 400 *USD/W* to 1000 *USD/W* in intervals of 100 *USD/W* and utility's tariff scenarios range from 94 *USD/MWh* (62 Chilean pesos per *MWh*) to 368 *USD/MWh* (242 Chilean pesos) in intervals of 30 *USD /MWh* (20 *pesos/MWh*) as shown in Fig. 4-7.

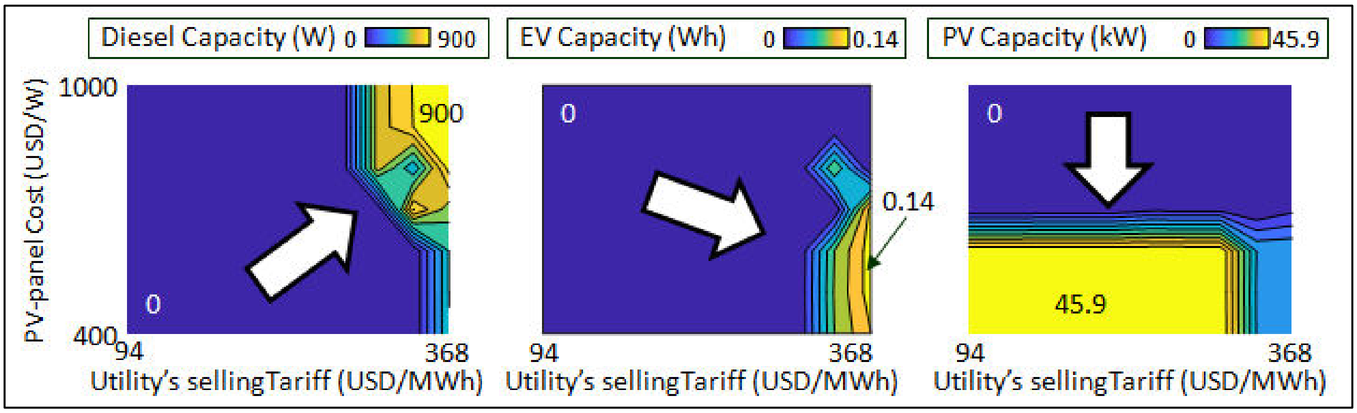


Figure 4-9: Which technology dominates? Which do not enter the market? Optimal microgrid's capacities of the technology-mixes of all 70 scenarios show that *PV* is the dominant technology. The second most used technology is diesel and only at very high utility's energy selling tariff. *EVs* are present only at very high utilitiy's energy selling tariff, low *PV* costs and with very small capacities. Gas- and wind turbines do not enter the market.

Technology mix rated capacities obtained for all scenarios behave intuitively with regard to tariff and *PV* panel cost. In general, *PV* is the dominant technology for a wide range of *PV* panel costs and tariffs. As expected, more *PV* capacity is installed with lower *PV* costs and also with increasing tariffs. *EV's* batteries and *PV* panels complement each other very well at high tariffs and at low *PV* costs due to price difference's arbitrage, and wind turbines as well as gas microturbines are unfeasible because of low wind resource and high capital costs respectively. Diesel generator capacity is only feasible at very high distribution tariffs. A selection of the capacity-mixes obtained for the scenarios studied are presented in Table 4-2 and can be visualized graphically for diesel, electric vehicles and *PV* technologies in Fig. 4-10.

As shown in Fig. 4-7, for all 70 scenarios five different technology mix types were found for the case of Diego de Almagro, counting from 0 to 4: 0) Unfeasible *μG*: *DERs* are unfeasible at *PV* panel costs around 1000 *USD/W* or above, and tariffs are below or equal to 155 *USD/MWh*; *DER* are also unfeasible when *PV* panel cost is above 0.7 *USD/W* and tariffs are at 125 *USD/MWh* or below; 1) *PV* only: *DERs* are composed only of *PV* capacity for all other cases beside the one indicated in 0) for tariffs equal and below 155 *USD/MWh*; for tariffs between 185 *USD/MWh* and 277 *USD/MWh* and; for tariffs at 307 *USD/MWh* or bellow and *PV* costs below 0.7 *USD/W*; 2) Diesel only: *DER* have only Diesel generation capacity if panel cost is above 0.6 *USD/W* and tariffs are at 307 *USD/MWh* with the exception of panels at costs between 0.6 and 0.7 *USD/W* and tariffs around 307 *USD/MWh*; 3) Diesel+*PV*: *DER* only have diesel and *PV* capacity for *PV* panel costs of 0.6 *USD/W* or below, and tariffs around 337 *USD/MWh*; 4) Diesel + *EV* + *PV*: For tariffs around 368 *USD/MWh* and panel costs of 0.6 *USD/W* and below diesel, batteries (*EV*) and *PV* would be deployed.

For all of the technology-mix types found for Diego de Almagro in Chile, a typical dispatch is also shown in Fig 4-7, which is representative of the technology mixes used. The increase in tariff, for example, due to the Death Spiral, changes the capacities installed and this can again change the tariffs as we show in this study. If the tariff change would pass a certain point a new technology could enter the market.

Total *DER* cost, including investment and *O&M* costs, were calculated for all scenarios. *DER's* total cost increases with both tariff and *PV* panel cost as expected, ranging from -5.94 *USD/W* for a panel of 0.4 *USD/W* and a tariff of 94 *USD/MWh* up to 10.40 *USD/MWh* for a panel of 0.8 *USD/W* and a tariff of 337 *USD/MWh* as shown in Fig 4-11. This also means that when *DS* increases distribution tariffs, more expensive microgrids become feasible. A negative cost means that *DER* owner will earn money by selling to the grid. This could be unsustainable if all end-users sell to the grid, unless the resulting power-flow is transported to regions without less favorable solar potencial and tariffs.

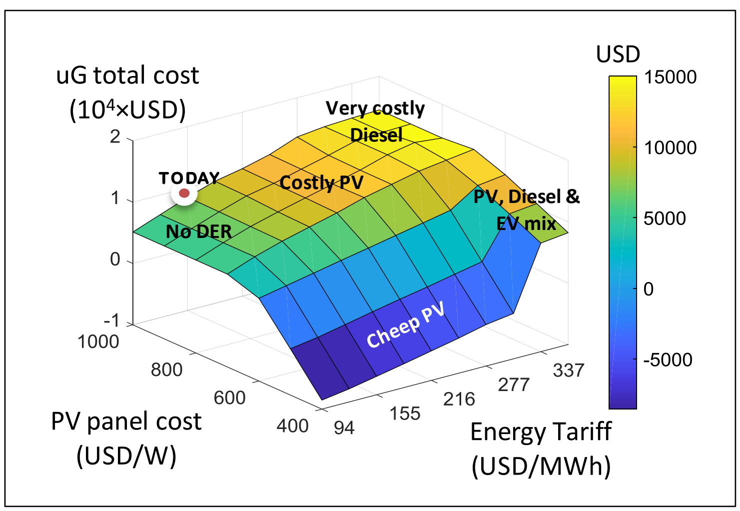


Figure 4-10: Total microgrid's for *DER*-owner. At today's low tariff and high *PV* cost no *DER* is installed (low and high are words only used in relation to the other scenarios). If tariff increases and *PV* cost remains high, costly *PV* will be installed. At

even higher tariffs and high *PV* cost, very costly Diesel will be installed. At very low *PV* costs, cheap *PV* is generally installed. Only at high tariffs and low *PV* cost do more complex technology mixes appear, e.g., *PV* + Diesel + *EV* (Note: low and high are words used here only in relation to the other scenarios presented).

Table 4-2: Technology-Mix Rated and Capacities obtained from selected scenarios with varying *PV* panel cost and Utility's selling tariff to end-user

PV panel cost (USD/Wp)	Utility's selling tariff to end-user (USD/MWh)	Diesel Generator's Rated Power (W)	PV's Rated Power (W)	EV's Rated Capacity (Wh)	Utility's selling tariff to end-user (USD/MWh)	Diesel Generator's Rated Power (W)	PV's Rated Power (W)	EV's Rated Capacity (Wh)
1	94.22	0	0	0	276.60	0	15401	0
0.9	94.22	0	0	0	276.60	0	10012	0
0.8	94.22	0	0	0	276.60	0	11493	0
0.7	94.22	0	0	0	276.60	0	34785	0
0.6	94.22	0	50773	0	276.60	0	50964	0
0.5	94.22	0	49969	0	276.60	0	50795	0
0.4	94.22	0	50275	0	276.60	0	50208	0
1	155.02	0	0	0	337.39	905	0	0
0.9	155.02	0	872	0	337.39	900	0	0
0.8	155.02	0	881	0	337.39	420	22255	0.100
0.7	155.02	0	888	0	337.39	905	0	0
0.6	155.02	0	50864	0	337.39	0	20400	0.100
0.5	155.02	0	50889	0	337.39	0	19816	0.103
0.4	155.02	0	51000	0	337.39	0	20154	0.100
1	215.81	0	895	0	367.78	940	0	0
0.9	215.81	0	895	0	367.78	951	0	0
0.8	215.81	0	11388	0	367.78	938	0	0
0.7	215.81	0	10012	0	367.78	645	38777	0.150
0.6	215.81	0	51000	0	367.78	500	20400	0.150
0.5	215.81	0	50657	0	367.78	501	20247	0.150
0.4	215.81	0	50847	0	367.78	498	20368	0.140

4.6.5 Utilities' bankruptcy risk due to missing tariff updates under *DER* penetration is distribution systems

Massive penetration of residential *DER* could rapidly become a major bankruptcy risk for utilities if no action to change tariff regulation is taken. If no regulatory change is made, during both *DER* penetration time-periods utilities could face significant bankruptcy risk due to 30.49% less income during the first 4 years from 22.72 *USD/month/customer* to 15.80 *USD/month/customer* and 47.04% for at least the next 6 years until 2028 from the same 22.72 *USD/month/customer* to 12.07 *USD/month/customer* as shown in Fig. 4-12. This risk is especially critical when considering that Chilean regulation, allows a return of 10% ± 4% (*LGSE*). A potential solution to reduce or eliminate this bankruptcy risk is to update the tariff to secure a stable and sustainable return for the utility. Another solution would be to design a tariff that decouples the network cost from the cost of generating energy.

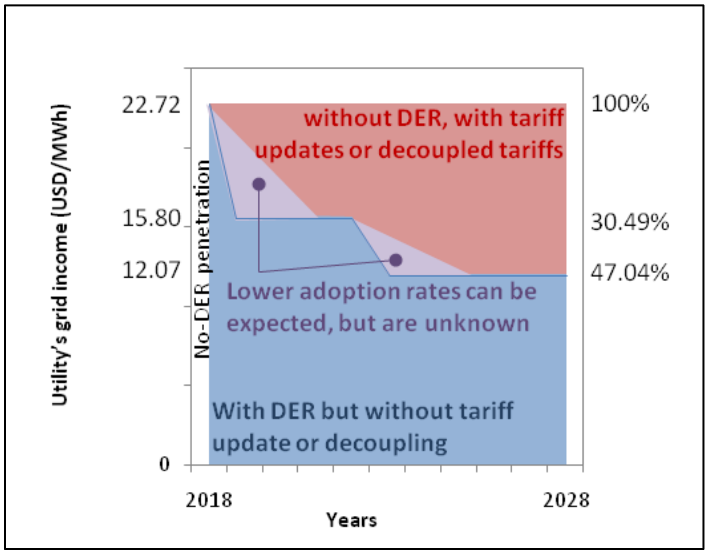


Figure 4-11: Will utility bankrupt due to *DER* penetration? Utility's grid income reduction may reach 47% in the long-run due to *DER* penetration if the regulator does not update tariffs or does not decouple network- and generation-costs. Because *DER's* adoption rate should be lower in practice, income reduction should be smoother.

4.6.6 If network tariffs are updated to secure utilities income: Development of a Death Spiral that could rise tariffs up to 24.35% in 10 years.

To avoid utility's bankruptcy risk when all households are deploying *μGs* (worst case), regulators could allow utilities to raise energy tariffs. This would develop a Death Spiral (*DS*) according to literature. In this case, our simulations show that grid-parity's breakthrough would be the triggering factor for *DS's* tariff increase. For Diego de Almagro, this increase would reach 12.30 %, stabilizing in 174 *USD/MWh* from 155.02 *USD/MWh* during the first 4 years where retrieving energy cost is higher than *PV* cost, but injecting energy cost is below *PV* cost. After that, tariff would rise even more, to accumulate a total increase of 24.35% and reaching 192.77 *USD/MWh* from the original 155.02 *USD/MWh*, at least during the next 6 years, where retrieving energy tariff and injecting energy tariff is below *PV* cost. This is shown in Fig. 4-13.

To obtain the final tariff increases, we have iteratively calculated the optimal local microgrid that an end-user would install with current tariffs and the optimal tariff increase to secure utility's income until a stable value is reached.

Besides the Death Spiral effect on residential tariff, the main problem with this tariff design is that low-income distribution system's end-users will tend to pay for the network cost. This happens because low-income households usually do not have the budget or credit capacity to purchase *DER* systems and thus do not have the chance to benefit from the higher tariffs.

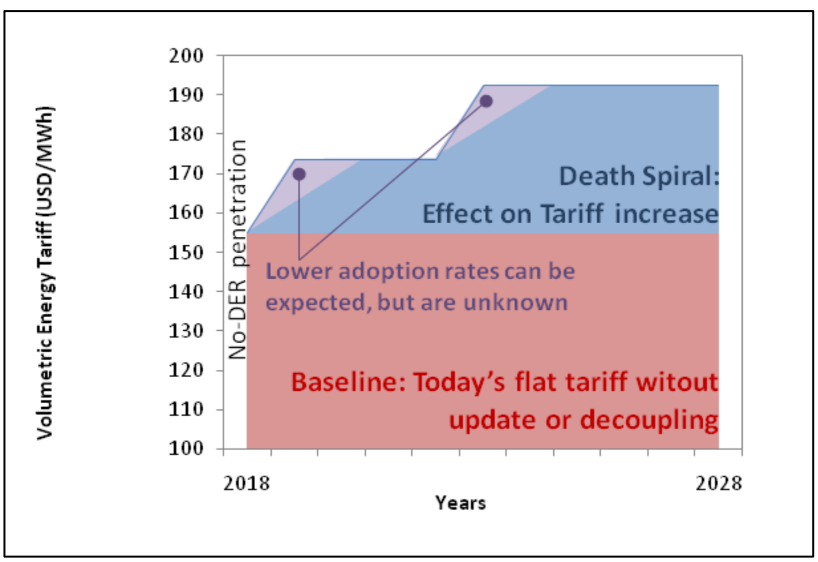


Figure 4-12: Will utility's selling volumetric tariff skyrocket? Tariff could increase up to 24.35% in the long-run from today's 155 *USD/MWh* to 193 *USD/MWh* if

regulator updates tariffs. Otherwise tariff remains invariant in time. Because *DER's* adoption rate should be lower in practice, tariff increase should be smoother.

4.6.7 A change to a two-part tariff design that decouples network costs from energy generation costs could negatively impact end-users who have already invested in *DERs*.

With a two-part tariff that decouples network costs from the energy generation costs, utilities may secure their profit and no unstable Death Spiral would increase tariffs. This gives certainties to both network-related and *DER*-related investments. Nevertheless, regulators should try to carefully choose exactly the moment when to change from today's volumetric energy tariffs design to a two-part design. Results show that if change is made earlier, when *PV* panel-costs are between 0.9 *USD/W* and 0.7 *USD/W* (first 4-year time-period) *PV* optimal installation of 877 *Wp* would not be adequate anymore, being optimal not to deploy *PV* at all. Nevertheless, for this earlier period the difference in optimal monthly cost before and after the tariff-design change that residential end-users will face should be marginal, ranging from 1.41% to 3.95%, which represents an increase in costs between 1.19 *USD/month* and 3.26 *USD/month* for each end-user. For the later period, when *PV* panel costs are between 0.6 and 0.4 *USD/W* (later time-period), the installed capacity of *PV* panels is the same; generation is being sold to the grid. Nevertheless, cost difference before and after the tariff-design change increases substantially compared to the preceding period from 15.35 *USD/month* to 17.43 *USD/month*. Thus, tariff design change will have a negative impact on *DER* owners. In turn, this would mean that a *DER* owner who saw *PV* deployment as economically optimal, before the change would afterwards partially regret those investments. Thus, potential *DER* investors may see this possibility as a regulatory risk, which may hinder *PV* deployment.

4.7 Conclusion

The path to the promised land of modern distribution system comes with a vision of massive, life-transforming, socially participatory, and sustainable deployment of new energy-services and technologies. Although this vision is being announced with bright colors, its path is full with pitfalls that regulators should be aware of in advance. This paper seeks to enlighten regulatory navigation and tariff design, showing possible troublesome scenarios that, once overcome, could make the original vision of a modern, efficient and fair distribution system possible.

We contribute to the literature not only by showing that the tariff design chosen is fundamental for a fair and economically efficient distribution system with massive residential *DER* penetration but also by demostrating that the moment chosen for the regulatory change is critical. Making correct - but late - structural changes to network tariffs may be as damaging as not making changes at all, especially in today's demanding society. Regulatory pitfalls may represent economical, societal and political risks for the regulator (and the government in charge), utility and end-users.

We also contribute by proposing a framework to model end-user decisions using a local microgrid optimization method. This framework reflects the behavior of an economically rational and inelastic end-user, which is the most extreme (worst-case) scenario from a regulatory perspective regarding *DER*'s adoption. Since it is very hard (if not impossible) for the current state of the art to forecast *DER* adoption accurately, a robust approach is to assume a simultaneous adoption of all users once a technology becomes feasible and economically viable (i.e. grid-parity is reached). Of course, this framework is only an approximation and reality should develop slowlier than predicted here, knowing all behavioral bias human beings have and all the technical, financial and economic and social restrictions homeowners face, e.g., loss aversion, status quo preference, credit limits or building shadows. Nevertheless, we think this is a very good starting point and benchmark for future studies.

Finally, we contribute by estimating the future evolution of residential *DER* penetration, tariffs and impacts on stackholders by extrapolating falling *PV*-price trends using learning curves.

4.7.1 Impacts on utilities and end-users: dependance on regulators decision to choose a particular tariff design scenarios and on timing of its change.

Tariff design changes may have a fundamental impact on all different stakeholders of a distribution system. In this paper we quantitatively show that depending on the tariff structure chosen, different stakeholders will be affected in dissimilar ways for the sunny town of Diego de Almagro in Chile, where the Chilean government is conducting studies for the development of a solar city that could be replicable in the rest of the country.

Here.we are considering a small utility that exclusively serves Diego de Almagro and that is fully financed by the rates charged to its customers. This is not exactly the case for this town but it serves to show a broader picture that can be of interest in many places. Nevertheless, specifically for Chile, the newly implemented tariff-equity law will slow down any possible Death Spiral since it forces electricity bills to be within 10% of the average national bill, establishing a cross-subsidy in favor of towns with high tariffs.

Our study analyzes the impact on utilities and households of three different tariff designs. These tariff designs are described below, delivering a brief analysis of the impacts for each stakeholder:

<u>Bundled volumetric energy tariff (Business as usual)</u>: Today residential tariffs are usually bundled into one value per unit of energy and tariff updates are not considered due to *DER* penetration (in Chile and several other countries). Under this regulatory scenario, our calculations estimate that PV should become feasible in just a few years, which would put pressure on the utilities' income, and thus would increase bankruptcy risk. For Diego de Almagro utility's income could fall more than 30% in just a few years and reach more than 40% within the next 10 years under full hyper-accelerated *DER* adoption. Because the unit of energy sold by the utility to the customer is more valuable than the energy bought from them since network costs are implicit, local production implies a cross-subsidy from the utility to *DER* owners, which would in turn speed-up *DER* deployment (in this case *PV*). Low-income end-users (who will not be able to install *DER* because of budget constraints) will be

indifferent because network tariffs and generation costs will remain the same for them.

Bundled volumetric energy tariff with yearly updates due to *DER* penetration: The regulator will most certainly avoid utility's significant bankruptcy risk of today's tariff design. One option regulators have to avoid this risk and secure a fair profit to distribution companies is to update tariffs yearly depending on the penetration level of *DER*[22]. As literature has identified, this will develop a Death Spiral, which is a positively reinforced loop that simultaneously increases tariffs when DER penetration increases, and increases *DER* penetration when tariff increases. A direct consequence of this tariff-increasing spiral is that potential investors will be more and more incentivized to install *DER*, which will speed up deployment even faster than with today's tariffs. The problem with this regulation comes for low-income end-users, which will subsidize *DER* owners because they will be obliged to pay for the increasing tariffs to secure utility's profit. Although regulators may wish to see fast and green *PV* deployment in distribution systems, tariff increases impacting on low-income end-users may become a moral and political problem, especially in low income areas

Two-part tariff that decouples network cost from generation costs: Another alternative to secure utility's profit but without affecting low-income users' bills due high-income users' *DER* deployment is to use a two-part tariff which could decouple network costs from generation-related costs. Under this tariff design, network

[22] *DER* penetration may be disruptive as has been experienced in some European countries, changing the distribution system landscape in one or two years completely. Thus, tariff updates due to *DER* penetration should be as close as possible in time and should not wait until traditional tariff process take place (every 4 years in Chile).

charges would be invariant in time for each user if losses are kept constant[23], despite DER penetration, which secures utility's income and avoids the evolution of a Death Spiral. Additionally, the volumetric per energy price that is part of this tariff design would be equal to marginal cost, which would improve economic efficiency significantly. Nevertheless, there are some undesirable impacts related to this design: i) a potential delay - for several years - of DER deployment, ii) the regulatory risk DER owners could face if tariff-design is changed after they have done their investment and iii) the distributional effect that the fixed cost of the two-part tariff has over end-users with different income levels (Borenstein & Davis, 2012; Fernàndez-Villadangos, n.d.).

4.7.2 Tariff design recommendations proposed for regulators

In light of our analysis for Diego de Almagro in Chile, we would recommend the implementation of a two-part tariff design as soon as possible for residential users (before *DER* penetration becomes significant) together with a low-income specific program. The two-part tariff design would guarantee cost recovery for utilities, avoid Death Spirals and improve economic efficiency when compared to today's tariff designs. This implementation should be done as soon as possible to avoid the negative impacts on people that already have installed *DERs*. The specific low-income program, e.g., income tax rebate, should guarantee a fair distribution of costs among users with different incomes without affecting economical signals (Borenstein

[23] IN this study we assume constant network losses. In real life network losses tend to decrease with increasing but small *DER* penetration and thus network costs tend to decrease as well. For large *DER* penetrations network losses increase with DER penetration, which implies that network costs also increase for those penetrations. In between there is a minimum-network-costs-point.

& Davis, 2012). Finally, it is also possible to complement this tariff design with some kind of benefit for PV installation for a few years in order to start deployment and overcome initial inertia. Nevertheless, we believe this subsidy should be well justified, maybe incorporating the cost of conventional generation's pollution into the marginal energy cost, which would benefit local *PV* systems (Borenstein, 2012). Nevertheless, these analyses are out of the scope of this paper.

Following this recommendation, regulators could mitigate political difficulties arising from a social opposition once penetration has become massive.

4.7.3 Proposition of a robust framework to understand end-user decisions for regulatory purposes: based on equally rational end-users optimizing their bills through both their connection to the grid and the installation of a local microgrid

International experience has shown that *DER* penetration in distribution systems can be disruptive and may happen in just a few years. Also, several studies highlight grid-parity as the key variable for *DER* deployment, which may be reached with subsidies or other financial incentives. This paper contributes by proposing a framework to model end-user decisions using a local microgrid optimization method. This framework would reflect the behavior of an economically rational end-user, which is the most extreme (worst-case) scenario from a regulatory perspective regarding *DER*'s adoption rate. Considering the difficulty current state of the art has to forecast *DER* adoption, it is only sensible and robust to consider a simultaneous adoption of all users once a technology becomes feasible (reached grid-parity).

Of course, the proposed framework based on extreme scenarios and economically rational end-users is only an approximation to reality, knowing all possible behavioral bias human beings have and future works should improve it. Thus, in practice a more smooth behavior of *DER* deployment should be expected due to some inertia due to other variables - besides grid-parity - such as hidden costs, environmental concerns, social networks and adopter categories, which were not analyzed here. Nevertheless, we think this is a very good starting point for robust regulatory decisions and should become a benchmark for future studies and policies.

4.7.4 The proposed framework's output: Prediction of the most feasible technology mixes and technology breakthroughs.

One of the most important advantages of the proposed framework is that it allows understanding the technology mix that would be most competitive in a distribution system and an estimated evolution in time (dominant, complementary and out-of-the-market technologies). We obtain this technology mix since our proposed framework is based on the optimization of a local microgrid for each distribution system end-user. Additionally we obtain the estimated evolution in time of this mix by extrapolating learning curves and production trends of technologies (i.e., for *PV*).

4.7.5 Massive penetration of *DER:* Significant impact on transmission systems.

The massive *PV* generation that should be seen within a decade or less in Diego de Almagro’s distribution system and probably also in all other northern regions of

Chile should impact transmission systems. If *PV* generation gets sold massively to the grid the distribution system will most probably transform itself into a virtual generator (at least for some hours of the year) composed of the aggregation of hundreds, thousands or even millions of small rooftop systems. This will have an impact on transmission system's operation and planning, which should be carefully studied in the future.

4.7.6 Main findings for Diego de Almagro: A town located in the north of Chile

For Diego de Almagro - a town with outstanding solar resources - we conclude that for a hyper-accelerated residential *DER* adoption, *PV* will most probably be the dominant technology and that a netbilling structure imposes a discrete two-period evolution of this PV penetration for today's bundled volumetric energy tariffs with or without updates due to *DER* penetration: i) at first *PV* will be deployed by end-users for self-consumption only and ii) after that end-users will install *PV* systems to additionally sell energy to the grid. This penetration is based on *PV* costs becoming cheap enough to avoid buying some energy from the grid and competitive enough to sell energy into the distribution system. For a two-part tariff, that decouples network costs from generation costs, *DER* penetration could only evolve in the second time-period because in this case the cost of buying energy from the grid is equal to the income from selling to the grid (per unit of energy).

Besides *PV* being the dominant technology, which should be deployed in two multi-year periods, we have calculated that small-scale residential *PV* systems should reach their tipping point to become feasible, probably in a couple of years. We have also confirmed that diesel generation is only feasible at high tariffs, which will mix with *PV* at low *PV* prices. Although our model concludes - from an electrical perspective - that *EV* would become feasible only at very low *PV* prices, high tariffs and with a very small capacity, they could be deployed anyway for the transportation services they would deliver. This could mean that *EV* should be seen in the future more as a load than as a battery from the grid's perspective.

It should be noted that the specific conclusions for Diego de Almagro should be analyzed with care. In general adoption rate and Death Spiral can be regarded as with a larger inertia than obtained here because of the following reasons: i) The utility of Diego de Almagro is not a small utility that serves only this town exclusively and is not financed fully only by its customers; ii) the newly implemented tariff-equity law was not considered; iii); adoption rate will be delayed by economical, technical and social restrictions as well as by human irrationality.

4.7.7 Future research: more consequences of *DER* penetration

Consequences of residential *DER* penetration are badly known and not well covered in literature. This is a research topic that should develop rapidly in the future. Reasons for this are i) the urgent need of regulators and industries, ii) the huge impact on millions of end-users and iii) the large amount of issues that have not been addressed yet.

Among others, one future research that is critical and complements with this study very well is on estimating potential markets for *DER* driven by all sources of technical end economical feasibilities. For example, ancillary services offered by Distributed Energy Storage Systems (*DESS*) or Electric Vehicles (*EV*) could be included into the proposed framework. Also alternative adoption rates should be studied, due to household barriers and behavioral biases. For example, these adoption rates could be driven by household income, elasticity, smart-meter roll-out, status-quo preferences or loss aversion, as well as subsidies and incentives.

Future research should extend this study by making it more accurate and reliable. This could be achieved by adding more temporal and special granularity to the grid's model. A complete grid model would allow studying the impact of *DER* on power flows, tariff process, price distribution and congestion management, as well as its effect on power losses.

We believe that higher *DER* penetration should imply a change in the direction of the power flow in the feeder, eventually increasing losses and thus increasing distribution network tariffs. At this point, a Death Spiral would be reinforced since more end-users would install *DER*. This should be researched in the future.

Another dimension of *DER*'s penetration is its potential effect on transmission systems. Once *DER* become massive, power flows could be reversed at the transmission level. Thus important consequences should be assessed in transmission expansion planning (*TEP*) and among distribution systems, e.g., with and without *DERs*.

5 CONCLUSIONS

The whole planet could benefit from the impressive paradigm shift that end-users of electricity may face massively in the future. This paradigm shift will change the way electricity is experienced by end-users, bring new and groundbreaking benefits to them. Today, this shift is already taking place, mainly in the developed world, due to economic incentives in favor of the environment, but it may soon spread into developing countries due to drastic cost reductions of microgrid technologies and Distributed Energy Resources (*DERs*), such as photovoltaic rooftops and batteries.

In this thesis we analyze this paradigm shift by focusing on the client, person, individual and citizen, who is the final electricity end-user behind the meter. This focus was centered on the end-user's particular benefits and preferences, recognizing their heterogeneity, and thus avoiding one unique and apparently optimal solution that would apply to all of them. Also, we highlight the different realities that distinct end-users may face.

Recognizing different realities is particularly relevant for renewable energies, where local conditions could change abruptly from one place to another, affecting not only the end-user that decides to invest in *DER* technologies, but also other agents such as project developers or institutional investors, for which risk has been modeled for example in the solar sector, even reducing their perceived risk through climate predictions.

Particularly relevant examples of specific end-user's realities are i) those connected to the grid in a modern and highly technologized society and ii) those rural and isolated communities who still have no access to electricity. In the first case, grid-tied end-users could benefit from the entrance of new and innovative energy-based services. In the second case, cost reduction of isolated communities' microgrids could allow access to electricity, improving their standard of living (e.g., healthcare, education and economy).

In this sense, it is important to notice that end-users - similar to generators - will maximize their individual benefit according to their preferences and realities, independent of the system's optimum and the global social welfare.

Our results suggest that photovoltaic systems (*PV*), which has been deployed massively in Europe, the *USA* and more recently in Asia, will remain a dominant clean technology for end-users worldwide. Throughout our research we recognize several key gaps in literature related to the future of end-users. Thus, we make some key contributions that could enable the shift of end-users' electricity paradigm: i) we propose a methodology to reduce financial risk of *PV* projects through the modelling of predictable components of solar radiation and 3 ocean-atmospheric oscillations. The methodology was developed for a large-scale *PV* plant but could be easily extended for rooftop *PV*, as well as for hydro, wind and other renewable resources. ii) We propose a methodology that offers a range of microgrid designs to an isolated community, where each of them is optimal for a particular consumption pattern and value of lost load. The community will have to choose the one that best suits their needs. iii) We propose a robust framework (worst-case) to understand the decisions of end-users to install *DER* using optimal μGs, thus quantifying the impact of different tariff designs and dissimilar regulatory decisions on end-users and utilities.

For all methodologies and frameworks, case studies were conducted in Chile, taking advantage of its outstanding solar resources.

The future of the electricity end-user seems to be divided into two realities: i) users who will gain access and reliability through isolated microgrids and ii) users who will be embedded into distribution grids with *DER* penetration and multiple energy services. What would be the optimal solution for a system that in the future would integrate these isolated grids into the distribution system? How should the integrated regulation be? A lot of questions are still open and it is impossible to know what will really happen, but we know enough to conclude that there is still plenty to do.

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