ON THE ECONOMIC VALUE OF RENEWABLE ENERGY COOPERATIVES

A MASTER THESIS BY

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PREFACE

DISCLAIMER

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Executive summary

Motivation

The world is in the middle of a transition to renewable energy sources. The integration of the new resources into the existing grids presents new challenges and opportunities. One recent development is the rise of renewable energy cooperatives across Europe. These cooperatives are organized in microgrids – subnetworks of the existing grids, comprised of households, distributed renewable energy generators (e.g. solar panels), energy storage and auxiliary components.

Technical aspects of microgrids have been covered thoroughly in recent literature. Some studies have focused on the social aspects of renewable energy cooperatives. However, little exists yet in the way of economic analysis of these cooperative microgrids.

Goal

This report aims to fill that literature gap by determining the net present value (NPV), discounted payback period and internal rate of return (IRR) of a mathematically modeled renewable energy cooperative. For comparison, these same metrics are provided for the same households operating solar systems individually. In addition, the influence of time-of-use rates, smart thermostats and feed-in rates on the financial metrics is examined.

Beyond the contribution to the academic literature on the subject, the findings are of importance to communities considering a renewable energy project, as a decision-making aid. Governments and NGO's may use the findings as a guidance in planning incentive structures for renewable energy investments. Finally, the results are relevant for many businesses in the renewable energy, utilities and smart grid electronics sectors, by serving as a starting point to improve their value proposition for this growing market segment.

Data

Data used in this report are all freely available for academic research through the Pecan Street project. The main dataset contains 2 years of hourly electricity generation and usage measurements of 128 households. This is further augmented by related metadata, survey results, and electricity rate structures for the local utility Austin Energy.

Methods

A mathematical model is described for the calculation of benefits at each hourly time interval. Installed costs are determined by approximation using the survey data. The resulting benefits pattern is projected for a time horizon of 25 years, using a combination of seasonal decomposition and autoregressive integrated moving average models. The resulting time series is then used to calculate the NPV, payback period and IRR for the cooperative.

To be able to compare different scenarios, confidence intervals for these metrics are determined. This is done through bootstrap resampling the households of the original dataset (with replacements) into 1000 new samples, then repeating the benefits calculation procedure of each. Confidence intervals (95%) for the parameters of interest are computed from the results, and used to compare the cooperative and individual scenarios.

Next, the above calculations are all repeated under a time-of-use utility rate schedule. The values are compared with those under the standard rates, and between the alternative scenarios.

The initial dataset is then divided into two groups based on the presence of one or more smart thermostats. Results are recalculated again and compared between the two.

To determine the influence of feed-in rates, this rate is varied manually, and the yearly rate of return is determined for each step. A linear regression model is fit to the results, with the confidence intervals of the coefficients again determined via bootstrapping. This is performed for both the cooperative and individual scenarios. Solving the resulting system of equations returns the breakpoint below which a cooperative is likely to be more profitable than the alternative.

Results

Findings obtained reveal a cooperative being highly profitable under given conditions, yielding an NPV between \$ 1 216 063 and \$ 1 835 522 based on a 6% discount rate. This represents a minimum advantage of \$ 204 494 over the individual scenario studied. The discounted payback period is estimated to lie between 4.24 years and 5.20 years, and the IRR between 21.83 and 28.78 % percent of the initial investment yearly. These numbers represent minimum advantages of -0.97 years and 2.89 % over the alternative scenario. It is concluded that the microgrid cooperative is likely to outperform the alternative, given additional up-front costs do not exceed \$ 204 494. If other advantages such as increased bargaining power and positive externalities are considered, the benefits of the cooperative scenario are amplified.

Application of time-of-use rates results in tighter confidence intervals for both the cooperative and individual cases. Consequently, the minimum advantages of the cooperative grow to \$ 251 113, -1.26 years and 3.47% for the NPV, payback period and IRR. However, the obtained intervals overlap with the results under the standard rates. Thus, it is not possible to conclude that either case will likely perform better or worse under time-of-use utility rates. The higher difference between the scenarios allows the cooperative a higher margin of safety for the initial investment outlay. Time-of-use rates are suggested to be a preferable option for utility operators, due to more predictable cash flows.

The presence of smart thermostats in households was not found to significantly impact the payback period and return rate of the cooperative. The conclusion drawn from this is that the effect of smart thermostats, if present, is too weak in magnitude to impact the long term model; however, the devices may hold merit from an individual households' perspective.

Two sets of linear models with corresponding confidence intervals were determined for the effect of feed-in rates on yearly returns of the cooperative and individual cases. Using those, a breakpoint is found at a feed-in rate of $ 0.1805 per kWh. At all lower rates, a cooperative microgrid is likely to outperform the alternative, all else being equal. A comparison is made between the breakpoint and individual rate of $ 0.1090, and between feed-in rates in other US regions. All but one of the compared rates are lower than the breakpoint, leading to the conclusion that the cooperative's comparative advantage is relatively robust for realistic values of the feed-in rate.

Evaluation of assumptions

Assumed investment costs are determined to be realistic, with the results also leaving margin for error. Based on limited data, the value differences are sufficient to justify the addition of microgrid components. Comparisons with other countries are difficult due to changes in every independent variable, yet cooperatives are expected to remain advantageous in the long-term scenario.

Recommendations

Suggested extensions of the model include more sophisticated dispatch algorithms and the addition of battery storage. The described model can also be used to study the influence of demographic variables and demand side management approaches. Finally, re-evaluating the model results on different datasets would be of great value.

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1 INTRODUCTION & RESEARCH QUESTION

The world energy supply is increasingly shifting towards renewable sources, motivated by concerns over climate change, peak oil demand and energy security. In particular, renewable energy sources are projected to make up between 26% and 34% of global electricity generation in 2040, depending on policies (IEA, 2015). These energy sources have certain characteristics that are going to impact the market structure of electricity generation in a significant way. In the case of solar and wind energy, two of their defining characteristics are modularity and intermittency.

The first, modularity, refers to the potential for efficient energy generation in small-scale installations, e.g. a single array of photovoltaic panels or a single wind turbine. This introduces the possibility of decentralized energy generation in locations that may or may not be connected to the utility grid. An emerging method for integrating these decentralized energy generators into the larger grid is known as the microgrid architecture.

The second characteristic of these energy sources, intermittency, refers to the varying output of solar and wind due to meteorological conditions, the seasons and the day/night cycle. This means that at times demand for electricity and the available supply may not be balanced. Several approaches and technologies are used to mitigate intermittency, for example: battery storage, smart grids, demand side management and combining different renewable sources.

Amid a growing amount of renewable, modular and intermittent sources in the global energy landscape, one recent development is the emergence of renewable energy cooperatives. Cooperatives can be defined as “an autonomous association of persons united voluntarily to meet their common economic, social, and cultural needs and aspirations through a jointly-owned and democratically-controlled enterprise” (ICA, 2015). In this case, the cooperatives are focused on the collective production, consumption and distribution of energy from renewable sources, most commonly solar and wind. Energy cooperatives provide their members with affordable and reliable energy, as well as addressing social, cultural and ideological needs. These cooperatives can be owned by businesses, individuals or a combination of the two. More than 2400 of these cooperatives have sprung up across Europe in recent years (Vansintjan, 2015), and thus they form an interesting and relevant topic for academic research.

This research is focused on the economic value that these energy cooperatives provide to the participants. While participants may have non-financial (i.e. ideological) reasons to organize these cooperatives, ultimately those are unlikely to form a sustainable solution unless they provide a surplus of economic value, compared to the alternatives (e.g. individual investment in solar panels). Energy cooperatives are a complex and multidisciplinary topic, and applied research from an economic perspective is lacking so far.

Cooperatives differ from traditional firms in microeconomics theory due to the fact that profit maximization is not the main goal. Furthermore, each member of a cooperative is allowed one vote for decision-making purposes, as opposed to publicly traded corporations where voting rights are dependent on the proportion of equity held. The behavior of participants in cooperatives is also more influenced by fairness concerns than it would be in traditional firms. The above three factors result in an effect on market structures that's profoundly different from traditional energy providers. Finally, it should be noted that the members may have non-economic reasons to participate in the cooperatives, such as ideological or social concerns (Yildiz et al., 2015).

The main research questions to be answered by this paper are:

1) What is the net present value of renewable energy cooperatives?
2) If the value is positive, what are the discounted payback period and internal rate of return for renewable energy cooperatives?

The above questions will be answered using publically available data from the Pecan Street project Dataport (dataport.pecanstreet.org). Different configurations of a cooperative microgrid will be mathematically modeled. Subsequently, appropriate time series analysis techniques will be used to determine the present value and payback period. According to the literature, some additional variables present in the data may have a significant impact on the present value. This has led to the following sub-questions:

a) How do different utility rate structures impact the present value and payback period?
b) To what extent does the presence of smart grid electronics such as Nest thermostats impact the payback period and return rate?
c) How sensitive is the yearly return to changes in the utility feed-in rates?

Applied research on this topic will be relevant for communities that are considering setting up energy cooperatives, and will provide guidance in determining optimal scale and scope of such efforts. Furthermore, policy makers may find the findings helpful in structuring initiatives supporting these renewable energy communities. Finally, the research may also be of use to utility companies and manufacturers of renewable energy equipment or smart grid electronics, as they may gain insights in how to improve their value propositions for cooperative microgrids.

2 Literature Review

2.1 The Energy Transition

In this chapter, the reasons for the transition toward renewable energy sources, as well as important characteristics of renewables and solar photovoltaic panels in particular, will be discussed.

2.1.1 Fossil Fuels

Fossil fuel based energy sources such as petroleum, coal and natural gas have been important drivers of economic activity in the industrialized world for over 150 years. Their relatively high energy density per unit of weight, and abundant availability has led to the above three fossil fuels accounting for 81% of the worlds energy supply as of 2015 (IEA, 2015). However, the use of fossil fuels has multiple associated problems. Three of the most important problems with their use are described below.

The first of those problems concerns the effects of geopolitical events on energy security. While the aggregate world supply of fossil fuels is sufficient to meet the demand for energy, "geopolitical factors nonetheless can constrain their timely availability" (Umbach, 2010, p. 1230). Examples of this can be seen in the effect on oil prices of the turmoil in the Middle East and the economic growth in Asia, as well as in the Russian-Ukrainian conflict disrupting the flow of natural gas to Europe (Yergin, 2006).

The second major problem lies in the fact that fossil fuel sources are finite and non-renewable resources. While rising oil prices can make exploitation of new oil fields economically viable, the amount of years before fossil fuel depletion is estimated at 35 years for oil, 107 for coal and 37 for natural gas (Shafiee & Topal, 2009), assuming consumption of them maintains 2006 levels. While other estimations arrive at different numbers, all confirm that fossil fuels will run out in the relatively near future. Seeing as how these 3 fuel sources make up a majority of the current energy supply, a replacement for them is needed.

The third problem with fossil fuels are their environmental effects and contribution to climate change. According to a 2007 report, carbon dioxide emissions are, at 63% the most important greenhouse gas in terms of radiative forcing, or warming the earth's surface. The majority of atmospheric CO_2 emissions are due to fossil fuel combustion, and thus decreasing dependence on fossil fuels appears to be necessary in order to stabilize radiative forcing (IPCC, 2007; Raupach et al., 2007).

Considering the three problems described above, it appears that diminishing reliance on fossil fuels would be beneficial for multiple reasons. As decreasing global energy consumption is undesirable due to adverse effects on economic activity, the need for alternative sources of energy becomes apparent.

2.1.2 Renewable Energy

A renewable energy source can be defined as a source of energy that can be continually replenished through natural processes, at a sufficient rate for continued usage (ISO 13602-1, 2009). Although fossil fuels are technically also renewable, the period for replenishment precludes them from falling under the above definition. The main renewables include wind, tidal, solar, hydro, geothermal and biomass energy sources (Ellabban, Abu-Rub, & Blaabjerg, 2014).

In contrast to the drawbacks associated with fossil fuels outlined in the previous section, the use of energy from renewable sources brings several key benefits (Dincer, 2000). The environmental impact of renewable energy sources is significantly lower than that of fossil fuel sources. The lifecycle emissions from fossil fuel energy generation is between 430-987 g of CO_2 per kWh of electricity generated; in contrast, emissions from renewables range from 7-167 g of CO_2 per kWh (Akella, Saini, & Sharma, 2009). It should be noted that there is no known energy source with zero environmental impact. However, a move to renewables would constitute significant harm reduction.

Furthermore, renewable energy sources are per definition not subject to depletion (with the possible exception of a hydroelectric reservoir being drained), as fossil fuels are. The concept of peak oil first appeared in 1956, and has reached general acceptance in the scientific community (Bardi, 2009). While estimates differ depending on the model used, global peak oil demand is currently estimated to occur around the year 2035 (Brandt, Millard-Ball, Ganser, & Gorelick, 2013). At that point, a transition to renewable energy sources is necessary and unavoidable.

A third benefit, which is of particular interest for the purposes of this paper, is the potential for decentralization and local energy solutions. As most renewable energy sources are site-specific, they appear inherently suitable for small-scale local projects. One key application of this is electricity generation in remote regions and/or developing countries. There is a high volume of research being done on the topic, although gaps still exist, in part due to cost data being scarce (Kaundinya, Balachandra, & Ravindranath, 2009). However, several case studies indicate that renewable energy sources are potentially feasible for these applications (Nguyen, 2007; Schneider, Duić, & Bogdan, 2007; Thiam, 2015). This area of research will be further explored in later sections.

The above benefits, coupled with the drawbacks of fossil fuels outlined in the previous section, have led to significant global investment in the research, development and deployment of renewable energy sources. In 2014, around 250 billion USD was invested in new renewable energy capacity. The majority of this amount was invested in solar photovoltaic energy, followed by onshore wind and hydroelectric energy sources. This continued investment has led to a lower cost gap between renewable energy sources and fossil fuels, and in certain locations renewable energy has become price competitive when compared to newly built fossil fuel plants (IEA, 2015).

Nevertheless, several barriers continue to oppose the widespread deployment of renewable energy. Those can be broadly categorized into economic and non-economic barriers. Economic barriers refer to instances where "the cost of a given technology is above the cost of competing alternatives, even under optimal market conditions, with a direct connection between technological maturity and economic barriers" (Ellabban et al., 2014, p.759). All other barriers are classified as non-economic, and examples of these include policy uncertainty, financing issues, and grid connection and integration issues (Kofoed-Wiuff, Sandholt, & Marcus-Moller, 2006; REN21, 2015).

2.1.3 Solar Photovoltaic Energy

Solar energy refers to "the use of the sun's energy to provide hot water via solar thermal systems or electricity via solar photovoltaic (PV) and concentrating solar power (CSP) systems" (Ellabban et al., 2014, p.752). Solar PV energy has the highest estimated technical potential for energy generation at 80 739 Mtoe (million tons of oil equivalent) in 2000 and 356 836 Mtoe in 2050 (de Vries, van Vuuren, & Hoogwijk, 2007). For comparison, the total world energy demand in 2013 was calculated to be 13 559 Mtoe (IEA, 2015, p. 69). It should be noted that technical potential is not the same as economic potential, which is defined as the energy generation potential at a cost competitive to the best local alternative. Actually achieving the technical potential, as given above, would require covering every suitable surface with solar PV panels. Nevertheless, based on the above data the potential of solar energy is evident.

Solar energy electricity generation technologies can be broadly categorized into PVs and CSP. While a detailed technical explanation of both is beyond the scope of this paper, it should be noted that they differ in the basic principles they use to convert the sun's energy into electricity. Photovoltaics work on solar radiation: they consist of "arrays of cells containing a material that converts solar radiation into direct current (DC) electricity" (Jacobson, 2009, p. 150). Meanwhile, concentrated solar power functions off heat: "sunlight is focused (concentrated) by mirrors … to heat a fluid in a collector at high temperature. The heated fluid … flows from the collector to a heat engine where a portion of the heat (up to 30%) is converted to electricity" (Jacobson, 2009, p. 150).

From this fundamental difference several advantages follow which make PV panels superior for usage in small-scale, decentralized applications such as energy cooperatives. First, PV panels allow for greater modularity, as depending on the number of panels they can be used in applications ranging from <10 kW to >100 MW, whereas CSP is only suitable for usage in plants above the 50MW threshold. Furthermore, PVs have the benefit of geographic independence, as they do not require direct sunlight as opposed to CSP. Finally, due to the leading cost structure of major PV panel manufacturers, the levelized cost of electricity (LCOE) per kWh is lower for PVs than for CSPs, regardless of plant location (Peters, Schmidt, Wiederkehr, & Schneider, 2011). As a result of the above collection of benefits, this paper will focus on solar energy from PV panels.

An important milestone for solar PV technology is grid parity. This is defined as the end user price for grid electricity being equal or more than the cost of electricity generation using PV panels, and is considered a sign of economic competitiveness with traditional power sources. Grid parity has already been achieved in at least 19 markets, and is projected for the majority of market segments in the world by 2020 (Breyer & Gerlach, 2013; Shah, Booream-Phelps, & Min, 2014). The upfront cost of a solar PV project is considered to be the majority of the lifecycle cost. This upfront cost consists of the cost of the PV modules themselves, and balance of systems (BOS) costs, for components such as inverters and cabling. As BOS costs constitute the greatest part of the upfront cost, reducing them through standardization and economies of scale is key to reaching grid parity.

Solar energy, like most other renewable energy sources, is inherently intermittent. PV panels produce no electricity at night, and during the day their output is dependent on atmospheric conditions. This forms a problem for the energy transition. If solar is to replace fossil fuels and nuclear power plants it needs to have the same reliability characteristics, in addition to being economically competitive (Cavallo, 2001). The problem of intermittence, as well as various solutions, will be further explored in subsequent sections.

2.2 Issues and Developments in Renewable Energy

This section provides an overview of issues and relevant research on renewable energy topics, with the focus on applicability in decentralized power generation settings.

2.2.1 *Intermittence*

The variable and seasonal output of renewable energy sources can result in a deficit in meeting electricity demand; in certain conditions it can also result in surplus electricity generation (Lund & Münster, 2003). Approaches for solving the intermittence issue have been well documented in literature. Broadly, they can be grouped in two categories: supply side approaches, providing additional energy to the grid, and demand side approaches which manage and shape the demand of electricity to match available supply. On a national level, geographical dispersion and improved weather forecasting have been shown to be effective in mitigating output volatility (IEA, 2005; Sovacool, 2009). However, these strategies are not applicable to regional grids, and thus will not be considered here.

The main supply side solutions include energy storage, supplemental power generation and grid interconnection. Cook et al. (2010) provide a review of energy storage technologies adapted to solar power generation. From all of the technologies reviewed, flywheel energy storage, batteries of various chemistries, ultra-capacitors and hydrogen fuel cells are considered to be the most viable in small-scale grids. Supplemental power generation refers to the practice of using a dispatchable energy source, most commonly diesel generators, to compensate for drops in electricity output. While diesel generators are a popular low cost option for stabilizing electricity output in standalone systems, "increased fuel prices, intensive maintenance and harmful carbon emissions … have made them unsustainable and unattractive" (Bajpai & Dash, 2012, p. 2927). Grid interconnection involves connecting the decentralized renewable energy system to the central utility grid. This allows both drawing additional electricity from the grid in case of shortages, and feeding surplus electricity back into the grid, effectively treating it as an unlimited capacity battery (Kaundinya et al., 2009). Due to the high cost of grid extension and the loss of energy in transport, grid interconnection is only suitable for areas close to the existing grid. The solutions mentioned above are not mutually exclusive, and combinations such as solar PV with a diesel generator and battery are commonly used.

Demand side management (DSM) techniques include both technological and economic strategies aimed at varying load in order to more closely match the amount power available. DSM techniques have already been applied in traditional energy grids to improve grid efficiency and reduce the required reserve capacity (Strbac, 2008). These techniques include energy efficiency programs for reducing energy demand in the long term, shaping consumer behavior through time-of-use electricity tariffs in the medium term, and dynamic Demand Response (DR) for short term capacity problems (Pina, Silva, & Ferrão, 2012). In the context of intermittency issues, DR is thus the most appropriate. Palensky & Dietrich (2011) distinguish between two types: market DR e.g. real time pricing, and physical DR e.g. direct control of appliances such as air conditioning. A form of market DR called critical peak pricing was found to be the most effective at reducing peak load, especially in the presence of enabling technology (Newsham & Bowker, 2010). The authors also found direct control strategies to be effective, but their usage is limited by the customers' tolerance.

2.2.2 *MICROGRIDS*

As mentioned above, many renewable energy sources are especially suited for decentralized use, in the form of distributed generators (DG). Existing electricity distribution networks were, however, designed around centralized power generation. Hence, the integration of DGs into the electric power grid has presented several new challenges, including "circuit protection coordination, power quality, reliability, and stability issues" (Ustun, Ozansoy, & Zayegh, 2011, p. 4031). The microgrid concept was introduced in 2002 by the Consortium for Electric Reliability Technology Solutions (CERTS) as a way to deal with these issues and facilitate the interconnection of DGs with the power grid (Lasseter et al., 2002). Microgrids are systems of DGs, distributed storage (DS) and customer loads that can operate both autonomously and interconnected with the grid at large. Renewable energy cooperatives are one of the practical applications of microgrids.

A typical microgrid includes four types of main components: DGs, DSs, an interconnection switch and control systems (Kroposki et al., 2008). DGs can be renewable sources such as solar PV panels or wind turbines, as well as gas microturbines and diesel generators. Some microgrid DGs provide power as well as heat, improving the energy efficiency of the system. DSs serve to protect against the intermittency of renewables, and balance load with power generation. Common DSs include flywheels, batteries and super capacitors. An interconnection switch toggles between autonomous (islanded) and grid connected modes, and as such must meet grid interconnection standards. Control systems manage the operation of the DGs and DSs, and handle disconnection and reconnection processes. In case of problems with the utility grid, sensitive loads such as medical equipment and servers are isolated from the main grid. Control systems can be either centralized or decentralized, depending on characteristics of the microgrid (Zamora & Srivastava, 2010).

Lidula & Rajapakse (2011) provide an overview of microgrid test systems in North America, Europe and Asia. They found that North American systems focus on decentralized controls and the reliability of the power supply, without using renewable energy sources. Experiments on various control configurations are done in Europe, and most DGs are renewable. The Asian test projects are unique in having a high number of industrial and commercial loads along with the residential ones, placing additional demands on stability. In terms of research goals, Ustun et al. (2011) underscore the importance of standardization and universalization, to avoid "re-inventing the wheel for every single microgrid project".

Renewable energy microgrids have other benefits associated with them beyond the easier integration of DGs into the electric grid. An overview of the different benefits is given by Morris, Abbey, Joos, & Marnay (2011). The authors have identified the following five categories of potential benefits for various stakeholders involved with a grid-connected microgrid.

- Reduced energy purchase: due to the presence of DGs, a microgrid supplies (a part of) its energy demand. Moreover, in many cases surplus energy can be sold back to the grid operator.
- Infrastructure investment deferral: a microgrid decreases demand on the electric grid through peak load reduction. This allows a grid operator to refrain from otherwise necessary investment.
- Reduced emissions: a microgrid generates energy from renewable sources, which otherwise would likely be purchased from fossil fuel plants. This benefits society at large.
- Ancillary services: depending on the installed equipment, a microgrid can provide various technical services to the grid operator, such as spinning reserves and voltage regulation.
- Improved reliability: by being able to disconnect from the utility grid, sensitive loads can be protected from outages.

2.2.3 *Energy Storage in Microgrids*

As mentioned above, distributed storage systems are an essential component of the microgrid architecture. Tan, Li, & Wang (2013) provide an overview of the main functions of DS in a microgrid application. In particular, DS can serve to diminish the issue of renewable intermittency through supplying additional power, maintaining power quality, and smoothing the transition from renewable energy sources to backup generators when needed. DS systems also compensate for the resulting temporary power shortage when a microgrid transitions between grid-connected and islanded modes of operation. Energy storage can provide a purely economic function too, in facilitating arbitrage. In many regions, time-of-use utility pricing is common, and the cost per kWh can differ substantially between on-peak and off-peak periods (Masters, 2013). In such cases, DS can charge when grid electricity is cheap, then discharge when it is expensive.

Current storage technologies commonly cited as technically appropriate for microgrids include batteries, fuel cells, supercapacitors and flywheels. Ibrahim, Ilinca, & Perron (2008) have compared these and other technologies on technical and economic factors. They found that fuel cells at this stage are expensive and have low efficiency, making them unattractive. Supercapacitors and flywheels are primarily useful for power quality functions, being cheap in terms of short term power output but prohibitively expensive for long term capacity. Batteries were found to be the only form of energy storage currently able to meet all microgrid demands. Another study (Nair & Garimella, 2010) assessed four common battery types (lead-acid, NiCd, NiMH and Li-ion) in a microgrid context. According to their findings, Li-ion type batteries show the highest potential, closely followed by NiMH batteries, provided their high initial costs can be brought down. Despite having inferior technical performance, at present lead-acid batteries are the most common, due to being cheap, widely available as well as fully recyclable. Dependence on them could present an issue in the future as lead reserves run out (Beaudin, Zareipour, Schellenberglabe, & Rosehart, 2010), further driving development of the newer battery chemistries.

A large amount of literature focuses on optimizing battery size and energy management in microgrids. A paper by S. X. Chen, Gooi, & Wang, (2012) confirmed that an optimum battery size exists, and differs based on whether the grid is operating in connected or islanded modes. The benefits of smart energy management were also examined (C. Chen, Duan, Cai, Liu, & Hu, 2011), with their simulation indicating potential savings of up to 28% depending on policy used. The difference between static and dynamic energy management has also been examined (Liu, Ding, Han, & Han, 2011). Static methods optimize for each individual time interval, while dynamic methods consider the benefit over a longer period. Their results show dynamic dispatch being particularly effective when a microgrid is able to sell power back to the utility grid, achieving cost savings of up to 38% compared to static methods.

2.2.4 SMART GRID TECHNOLOGY

'Smart grids' is a term commonly mentioned in recent academic literature on the integration of renewable energy sources. Fang, Misra, Xue, & Yang (2012, p. 944) define the smart grid as "…an electric system that uses information, two-way, cyber-secure communication technologies, and computational intelligence in an integrated fashion across electricity generation, transmission, substations, distribution and consumption to achieve a system that is clean, safe, secure, reliable, resilient, efficient, and sustainable". For electricity consumers and generators, the most important feature of smart grids is the installation of smart meters (Clastres, 2011).

Smart meters offer many advantages over conventional electricity meters: they allow for real-time registration of electricity use and generation, remote reading and throughput limitation, and interconnection to other devices (Gerwen, Jaarsma, & Wilhite, 2006). Smart meters are often (but not always) used in combination with smart thermostats and/or in-home displays. The large volume of data generated by smart meters allows for better market analysis and demand forecasting by utility companies. Moreover, smart meters also enable the use of demand side management techniques and thus can help with renewable intermittency.

Quite some research has been done on the electricity savings and peak load reduction enabled by smart metering. Just the feedback provided by smart meters has been shown to result in a 10 to 13% reduction in electricity usage in households overall (Gans, Alberini, & Longo, 2013). Another study found that the addition of enabling technologies like smart thermostats and in-home displays makes feedback more effective, citing peak load reductions of 15% on average (Ivanov, Getachew, Fenrick, & Vittetoe, 2013). Beyond just providing feedback on consumption, smart meters also facilitate the use of dynamic pricing strategies and direct load control. Olmos, Ruester, Liong, & Glachant (2011) compared the effectiveness of all three above methods in Austria. Their findings show that dynamic pricing methods are the most effective at peak load reduction, especially in winter. As for long term energy savings, these authors also found feedback to be the best strategy, with advanced feedback packages performing better than simple ones.

Smart grid technologies are not limited to electricity metering. Another closely related technology that has emerged in recent years is the smart thermostat, with the Google-owned Nest being the most prominent example of this product category. Beyond providing a better user interface, smart thermostats leverage recent advances in machine learning to optimize the operation of heating and cooling systems in the house. Theoretically, this should result in energy savings without sacrificing comfort. A recent whitepaper by Nest reports obtained savings of 15% of total cooling electricity use on average, or 585 kWh per year (Nest Labs, 2015). Kleiminger, Mattern, & Santini (2014) compared several of the algorithms smart thermostats use to determine home occupancy. The authors found potential energy efficiency gains between 6 and 17%, with the savings being higher for homes with worse thermal insulation.

2.3 Renewable Energy Cooperatives

Here perspectives on cooperatives in academic literature are presented, and their relevance in the context of renewable energy is discussed.

2.3.1 Energy Cooperatives

Electric cooperatives are not new. In the case of rural electrification, which is unattractive for private firms due to low profitability, local cooperatives have often successfully filled the market gap (Yadoo & Cruickshank, 2010). This is made possible by the fact that a cooperative's primary goal is not profit, but rather increasing the welfare of its members. For renewable energy, the cooperative form has several advantages, as outlined by Huybrechts & Mertens (2014). It provides transparency, fosters social acceptance of renewable energy sources, and oftentimes achieves lower electricity prices. However, it also faces a number of barriers in "limited access to capital, few locations, consumer inertia and lack of public support" (p. 208), as well as a lack of understanding of the cooperative model.

Despite these barriers, a large number of renewable energy cooperatives have been founded in recent years, most of them in Germany and Denmark. A number of characteristics of the new German cooperatives are provided by Yildiz et al (2015). Most of the cooperatives focus on the generation of energy, with a comparatively small amount focused on distribution and trading. Of the generation cooperatives, 75% are making use of solar photovoltaic panels. The majority of the cooperatives are small: 65% has less than a million euro in capital, and 50% has between 3 and 100 members. Furthermore, the cooperatives have relatively high equity ratios, with a quarter of them being 61% - 100% equity funded. In terms of demographics, the vast majority is older than 35, and their monthly income is skewed upwards of the national average.

Müller and Rommel (2010) have investigated the reasons for the success of the Greenpeace Energy cooperative in Germany through a case study. The main factors identified as important from a combination of document analysis and interviews were differentiation and consumer-producer interactions. Differentiation refers to the demand for green energy: cooperatives reduce information asymmetry for consumers on the origin of the energy supply. Consumer-production interactions are becoming more important due to smart grids and variable tariffs. As Müller and Rommel (2010) state, "assigning ownership of an electricity utility to customers lowers the costs of obtaining customer information".

Some current research has focused on consumers' willingness to pay a premium for energy from renewable energy cooperatives. The findings of Sagebiel, Müller and Rommel (2014) indicate that consumers exhibit a large willingness to pay (WTP) for energy from renewable sources, as well as a medium WTP for transparency, participation in decision making and local suppliers. This may explain the recent surge in energy cooperatives, despite the fact that little research has been conducted on their economic value.

2.3.2 Cooperatives in Economic Literature

The theoretical foundation for organizing transactions outside of market mechanisms was first laid by Coase (1937). As he showed, conducting transactions on the open market involves transaction costs, which may be lowered by conducting these transactions within a hierarchical organization form such as the firm. These transaction costs are dependent on three properties of the transaction, those being frequency, uncertainty and specificity. Due to the profit incentive for lowering these transaction costs, an optimal organization structure will emerge where possible. In some industries like farming, wholesale, utilities or insurance, with certain market conditions, cooperatives can be optimal (Hansmann, 1988).

Cooperatives can be viewed as a hybrid form between market transactions and a hierarchical organization. While members contribute resources into the cooperative business, internalizing transactions and "utilizing transaction-specific assets without depending on outside companies" (Bonus, 1986, p. 334), they retain their economic independence and are able to use their resources for other purposes as well. Agriculture is a field where cooperatives are a common organizational form. Valentinov (2007) has shown that this can be explained by two disadvantages inherent to family farms: their inability to leverage economies of scale for lower costs, and their limited market power compared to up- and downstream trading partners. The impact that the presence of cooperatives has on the market at large is described by the competitive yardstick theory (Cotterill, 1987). The theory states that the presence of cooperatives in an oligopolistic or oligopsonistic market leads to more competitive markets, as the prices of other buyers/sellers tend to the level set by the cooperative. Some empirical support has been found for the theory in both coffee purchasing and dairy marketing cooperatives (Hanisch, Rommel, & Müller, 2013; Milford, 2012).

Cooperatives typically involve joint ownership of assets and sharing of profits by their members. This is incompatible with the self-interested view of contract theory, which states that joint ownership allows for opportunistic behavior, and is therefore not optimal for any of the parties involved. Fehr, Kremhelmer, & Schmidt (2008) have disputed this, demonstrating that joint ownership is the optimal structure if at least some of the players show a preference for fairness. Cooperatives satisfy this condition, as a tradition for fairness is one of their defining characteristics (Bonus, 1986). Furthermore, joint ownership of assets logically leads to democratic decision-making processes. Policies established through a democratic process are found to be more effective (Dal Bó, Foster, & Putterman, 2010). The authors have shown that this is not simply a result of increased informedness, and the same individuals behave differently if the rules of the game were chosen by themselves instead of external parties. These findings from behavioral economics are helpful in explaining the effectiveness of cooperatives as an organizational form.

An issue in worker cooperatives is members not contributing their fair share, in a process known as shirking. Shirking can be avoided by monitoring, but the lack of hierarchical structure in a worker cooperative means that mutual monitoring is less effective (Ben-ner & Ellman, 2013). The authors propose a set of selection processes for members that are less likely to engage in shirking. In the case of a renewable energy cooperative, near-perfect modeling can be provided by smart meters, as described above. With real-time production and consumption data, identifying members who take more or contribute less than their fair share is simple.

2.3.3 *COOPERATIVES IN SOCIAL SCIENCES LITERATURE*

Organization by the local community can provide multiple benefits to renewable energy projects (Walker, 2011). The residents identify with the local projects, and are educated about renewable energy by their presence, making them more likely to join. The community also can function as a source of innovation, made possible by the assembled skills and knowledge of its members. Setting up and managing such a project is a difficult endeavor, particularly in the area of obtaining equity funding. This means that most of the successful projects are dependent on partnerships with local organization, and access to expert support. The situation is not unique to renewable energy, as obtaining financial, intellectual and political capital are some of the key issues all cooperatives must face (Daudi & Sotto, 1986). The barriers to obtaining grant funding for community energy projects are underscored by Park (2012). The author cites the complexity of the grant application process and a preference for established organizations with higher cost effectiveness as some of the issues.

Much of the literature on cooperatives focuses on their governance and control structures. In principle, a cooperative has direct member control according to a one-member-one-vote principle. In practice, this is unworkable beyond a small amount of cooperative members, and thus a typical cooperative at some point democratically elects a board of directors (Chaddad & Iliopoulos, 2013). Formal authority is thus delegated to the board, which presents a paradox. This board has both a conformance and a performance role, that is: it is tasked both with driving firm performance, and looking out for the members' interests (Cornforth, 2004). Those roles frequently conflict resulting in high decision-making cost, prompting some scholars to argue for a more corporate governance structure with professional management taking over the performance role (Davis, 2001). The effectiveness of such a structure hinges on the homogeneity of members' transactions and goals, and the ability to set appropriate performance measures for the management team (Chaddad & Iliopoulos, 2013). This inherent contradiction between hierarchy and democracy has empirical support, e.g. in the case of a Mexican industrial cooperative (Hernandez, 2006). The author notes that cooperatives should not be viewed as a democratic utopia. Instead, they need to decide on a pragmatic governance structure appropriate to their situation, like all other organizational forms should.

Trust is another related concept. Dirks & Ferrin (2001) have examined the impact of trust on the functioning of an organization. They propose that trust has a mostly direct effect on outcomes in settings where participants have highly mixed incentives; when motives are mostly homogenous, trust functions more as a moderator for other variables. The members of a cooperative have a common goal in maximizing their collective welfare, which implies trust would have a moderating function. And indeed, trust has been found to have a strong positive effect on commitment (Barraud-Didier, Henninger, & Akremi, 2012) and group cohesion (Hansen, Morrow, & Batista, 2002) which are linked to performance and member satisfaction. Research on how trust itself is formed in cooperatives was done by Borgen (2001). In the study, member trust in cooperatives was mainly determined by identification with the cooperative: how much they consider themselves a loyal member, and whether they have acted as a representative. In the context of community renewable energy projects, trust was found especially vital for the success of project development (Walker, Devine-Wright, Hunter, High, & Evans, 2010). The authors note that "community cohesion and trust between local people and lead groups is not universally ensured just because a project is given a community label" (p. 2662).

3 METHODOLOGY

This chapter describes the approach used to answer the research questions defined in the introduction chapter. It provides a more exact definition of the problem statement, a description of the dataset and a brief overview of the calculations and statistical methods employed. All calculations are performed in the R programming language, and all the source code used is available upon request.

3.1 PROBLEM STATEMENT AND ASSUMPTIONS

The main research questions defined in the introduction chapter concern the economic value of renewable energy cooperatives. Here the questions, underlying definitions and assumptions are further specified, so that they can be answered unambiguously.

1) **What is the net present value of renewable energy cooperatives?**
2) **If the value is positive, what are the discounted payback period and internal rate of return for renewable energy cooperatives?**

The economic value of a renewable energy cooperative is the sum of the benefits received from it minus the sum of the costs, during the entire economic lifespan of the grid. For the purposes of this paper, we will only consider the monetary value for the members of the cooperative. Non-monetary effects and/or externalities are not discussed. The economic lifespan of solar PV modules is frequently considered to be around 25 years, with many manufacturer warranties being valid for this duration (Azzopardi & Mutale, 2010; Branker, Pathak, & Pearce, 2011; Kannan, Leong, Osman, Ho, & Tso, 2006). As such, the time horizon for the cooperative will also be considered 25 years.

The benefits from the cooperative consist of savings and revenue. Savings are realized by using generated electricity that would otherwise need to be purchased from the electric utility. They are valued at the appropriate electricity tariff (City of Austin, 2015a) for the time period when the savings occur. Revenue is realized by selling surplus generated electricity back to the utility. This is valued at a constant feed-in rate (City of Austin, 2015b).

The costs of the cooperative consist of the initial installed cost of all solar PV systems, plus the cost of all secondary micro-grid components, project cost and construction, operations and maintenance. For the calculations, only the installed cost will be considered, as there is no reliable source or method to estimate the other added costs. A cooperative will be said to have positive value so long as the additional costs do not surpass the difference from the next best alternative. The installed cost of generation can be estimated through multiplying the total PV capacity for the cooperative by the 2012 median reported price per watt for systems between 5 – 10 kW from a US government report (Feldman et al., 2013). The cost of electricity that was purchased from the grid is <u>not</u> included in the calculations, as this cannot be attributed to the PV system or micro-grid.

The economic value is estimated for the entire 25-year time horizon using the procedure described in the next sections. From this, a confidence interval can be constructed for the net present value (NPV) of this cooperative, as well as the discounted payback period and the internal rate of return (IRR). The time horizon is computed using an interest rate of 6%; These numbers will subsequently be compared to the NPV, payback period and IRR of the next best option: all members running individual PV systems, without micro-grid infrastructure present.

a) How do different utility rate structures impact the present value and payback period?

The local electric utility has two different tariff structures, which their customers are allowed to choose between (City of Austin, 2015a):

- Under the default structure, the electricity tariff is determined by 2 variables: the season and the total electricity usage for the current month. Furthermore, the tariff includes a static component.
- The time-of-use structure adds two more variables: the time of day and the day of week. Different rates are applied for on-peak, off-peak and mid-peak periods. The static component remains the same.

The NPV, discounted payback period and IRR will be calculated under both tariff structures and compared.

b) To what extent does the presence of smart grid electronics such as Nest thermostats impact the payback period and return rate?

One of the main selling points of smart grid components such as smart thermostats is the promise of energy savings, and studies report achieved savings between 10 and 28% (Agarwal et al., 2010; Lu et al., 2010). In the dataset, for each household the amount of installed smart Nest thermostats is reported. Using this information, the NPV and payback period is compared between households with 0 smart thermostats and households with 1+ smart thermostats installed.

c) How sensitive is the yearly return to changes in the utility feed-in rates?

To answer this question, the feed-in rate will be manually varied and the effect on the yearly return rate will be recorded. This will allow to determine the linear coefficients of the regression of the yearly return rate on the feed-in rate. For this sub-question, only historical data will be taken into account.

3.2 Description of the Data

The research questions will be answered using publically available data from the Pecan Street Project. The Pecan Street Project is an energy research collaboration between the city of Austin, the university of Texas, and various corporate partners and NGO's. They provide an enormous dataset on solar energy production and consumption of project participant households at 1 minute, 15 minute and hourly resolution, as well as other potentially interesting data. Variable definitions are found in the dataset description (Pecan Street Dataport, 2014). Furthermore, various analyses, additional data and background information can be found in the final technology performance report (Pecan Street Smart Grid Demonstration Project, 2015).

For this research, the hourly resolution Pecan Street dataset was selected, and filtered to only include the households with rooftop solar PV systems installed. As is to be expected, during the course of the Pecan Street project the number of participants varied. In particular, the number of participants grew strongly during the first two years, leading to a much greater amount of data being available for 2014 and 2015. Only households which were present for the entire period are considered, to eliminate the effect of households joining and leaving on the forecasts.

Due to the above, a trade-off had to be made between less households with a longer time horizon on the one hand, and more households covering a shorter period on the other. In more practical terms, this meant choosing between 3 years of observations for 99 households and 2 years of observations for 128 households. After careful consideration, the decision was made to use the latter option. This is due to the fact that the annual production and consumption patterns vary more between different households than they do between years for the same household (see Figure 1 and 2 for an example).

The main variables of interest in the dataset are ***gen***, which is the amount of power generated by a solar PV system over the time interval by a particular household, and ***grid***, which is the amount of power drawn from (+) or sent (-) to the utility grid. The sum of those, ***use,*** is the total electricity consumption over the interval. The other variable used in the analysis is ***number_of_nests***, indicating the amount of Nest smart thermostats installed.

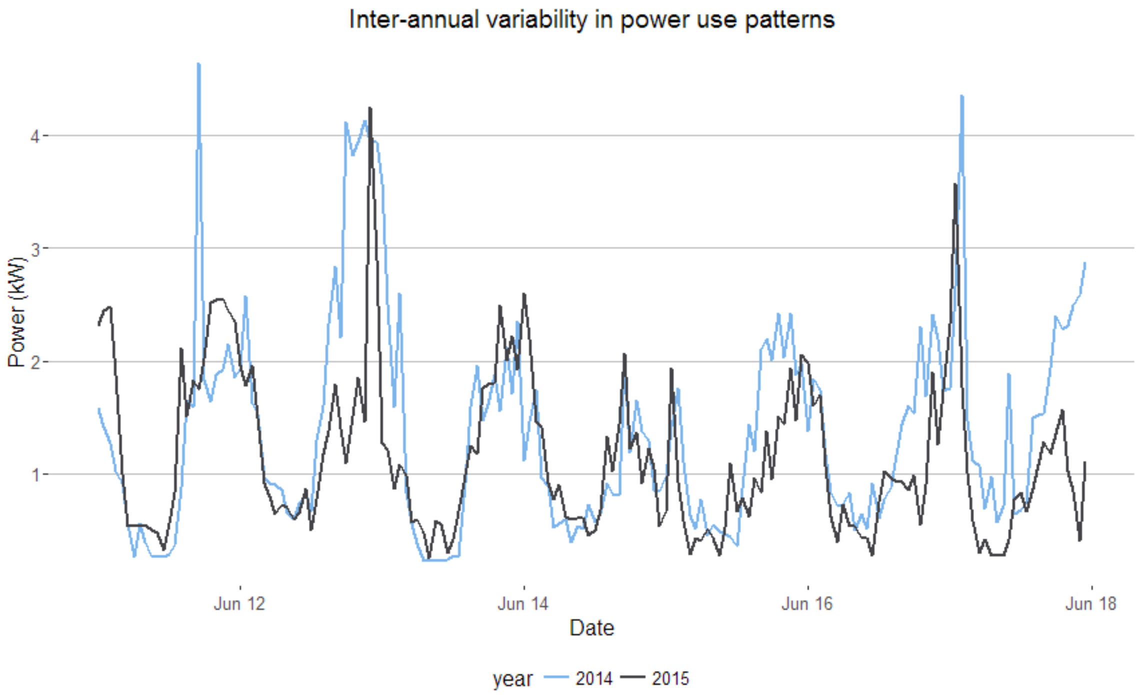

Figure 1: The power use of one household, during week 24 of 2014 and 2015. The date axis uses 2014 dates.

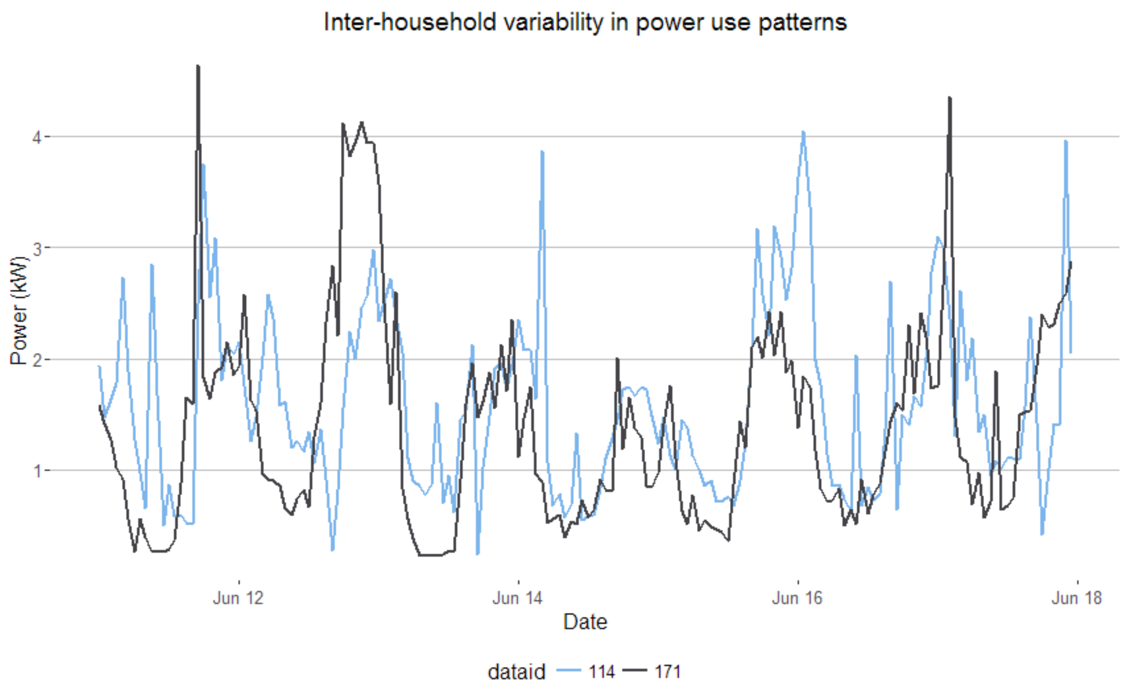

Figure 2: The power use of two different households in week 24 of 2014.

The final dataset that was used to answer the research questions consists of 17533 hourly observation of ***grid, gen*** & ***use*** for 128 different households. The number of observations is equivalent to 2 years of hourly data, with a year considered to be 365.25 days to account for leap years. Furthermore, metadata for each of the participating households and demographic surveys for 2013 and 2014 were used.

3.3 Value Calculations

For the purposes of the economic value calculations, we will define a renewable energy cooperative as a microgrid with rooftop solar PV DGs and some form of short-term DS that allows members to use surplus power produced by others (but not store it for use in subsequent time periods). In certain situations, it may be more profitable for the cooperative to sell the surplus power rather than use it to supply a member's deficit. However, this will not be done, as "it is the co-op's purpose to maximize welfare of its members, not to maximize income (at member expense) at the co-op level" (Sexton, 1986).

3.3.1 The Cooperative Model

Economic value was defined as the benefits minus the costs. The benefits are (potentially) obtained at each time period. The cost is the initial investment cost. By subtracting the initial costs from the present value of the benefits, a total NPV can be obtained:

$$NPV = PV_B - C_I \qquad \textbf{(1)}$$

The present value of the benefits is calculated by discounting each benefit cash flow $\boldsymbol{B_t}$ by the discount rate $\boldsymbol{r}$ for the corresponding period $\boldsymbol{t}$ up until time horizon $\boldsymbol{T}$, which can be noted as:

$$PV_B = \sum_{t=0}^{T} \frac{B_t}{(1+r)^t} \qquad \textbf{(2)}$$

The benefits for the cooperative consist of aggregate surplus energy $\boldsymbol{S_t}$, multiplied by the feed-in rate $\boldsymbol{P_S}$ plus aggregate generated energy $\boldsymbol{G_t}$ multiplied by the appropriate utility tariff $\boldsymbol{P_{G,t}}$. (See section 3.3.3 for details on how $\boldsymbol{P_{G,t}}$ is determined.) Here a single household is denoted as $\boldsymbol{h}$, and $\boldsymbol{H}$ is the set of all households in the cooperative.

$$B_t = \sum_{h \in H} S_t \times P_S + \sum_{h \in H} G_t \times P_{G,t} \qquad \textbf{(3)}$$

For each individual household $\boldsymbol{h}$ in cooperative $\boldsymbol{H}$, surplus energy $\boldsymbol{S_t}$ and generated energy $\boldsymbol{G_t}$ are determined as:

$$\forall h \in H, \qquad S_t = \begin{cases} |grid_t| & \text{if} \quad grid_t < 0 \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

$$\forall h \in H, \qquad G_t = \begin{cases} use_t & \text{if} \quad grid_t < 0 \\ gen_t & \text{otherwise} \end{cases} \tag{5}$$

The initial investment cost $\boldsymbol{C_I}$ is determined by the total installed cost of solar PV systems $\boldsymbol{C_{PV}}$:

$$C_I = \sum_{h \in H} C_{PV} \tag{6}$$

The main Pecan Street dataset does not contain per-household data on installed solar capacity or cost. The demographic surveys from 2013 and 2014 do contain this information; however, they're not available for every household. Therefore, a way to approximate the installed capacity was devised as follows.

A solar PV installation will not perform at nameplate capacity in reality, because of the various efficiency losses that occur. A discussion of these losses is beyond the scope of this research; however, several reviews of various losses are available in recent literature (Mekhilef, Saidur, & Kamalisarvestani, 2012; Meral & Diner, 2011; Omubo-Pepple, 2009; Skoplaki & Palyvos, 2009; Vignola, Mavromatakis, & Krumsick, 2008). Therefore, the ratio between maximum ***gen*** and reported installed capacity was calculated for the households that had survey data available (n =99). After excluding outliers, a 95% CI [0.84, 0.86] for the mean ratio was found. Consequently, a 0.85 ratio was used to estimate the installed capacity.

To determine the cost $\boldsymbol{C_{PV}}$, the installed solar PV capacity was multiplied by the average price per watt peak ($5.1) for residential systems from a U.S. government report (Feldman et al., 2013). Furthermore, the systems in the Pecan street project were on average subsidized at 84% through several rebates; this is also taken into account. All of the above gives:

$$\forall\, h \in H, \qquad C_{PV} = \frac{\max(gen)}{0.85} \times 5.1 \times (1 - 0.84) \tag{7}$$

The ***discounted payback period*** is defined as the number of years that has passed before the cumulative sum of discounted benefits surpasses the initial investment amount. This can be written as:

$$Payback\ period = T \text{ for which } \sum_{t=0}^{T} \frac{B_t}{(1+r)^t} - C_I \geq 0 \qquad \textbf{(8)}$$

Finally, the internal rate of return (IRR) is obtained by setting the NPV to zero and solving for the discount rate $\boldsymbol{r}$ in formula (1).

3.3.2 The Individual Model

As mentioned in the problem definition section, the results of the cooperative will be compared against the results of the next-best option, which is defined as the same households with rooftop solar PV operating individually. The difference between the two can be considered as the opportunity cost of the cooperative.

In this case, benefits are calculated separately for each household, then aggregated afterwards. Formula (3) is thus replaced by:

$$B_t = \sum_{h \in H} B_{h,t} \qquad \textbf{(9)}$$

Here, the benefits for each household $\boldsymbol{B_{h,t}}$ are calculated as:

$$\forall\, h \in H, \qquad B_{h,t} = S_t \times P_S + G_t \times P_{G,t} \qquad \textbf{(10)}$$

The rest of the formulae remain the same as for the cooperative model.

3.3.3 Electric Utility Tariff and Feed-in Rate

The feed-in rate P_S at which surplus generated electricity that is sold to the grid is valued, is initially set to \$0.109 per kWh (City of Austin, 2015b). For the cooperative model the utility tariff $\boldsymbol{P_{G,t}}$ is dependent on the monthly running total of grid electricity use $\boldsymbol{U_t}$, defined as:

$$U_t = \sum_{h \in H} grid \geq 0, \text{ for } grid \text{ in the current month up until now} \qquad \textbf{(11)}$$

In the individual model, $\boldsymbol{U_t}$ is determined separately for each household, replacing formula (10) with:

$$\forall\, h \in H, \qquad U_t = \sum grid \geq 0, \text{ for } grid \text{ in the current month up until now} \qquad \textbf{(12)}$$

Under the standard rate schedule, the appropriate utility tariff $\boldsymbol{P_{G,\,t}}$ is selected from the schedule in Table 1 at each time interval according to $\boldsymbol{U_t}$ and the current month, and $0.05107 is added to this tariff. The latter value represents the sum of various regulatory and miscellaneous charges that do not vary with usage tier.

Season	0 - 500	501 - 1000	1001 - 1500	1501 - 2500	>2500
Summer (Jun – Sep)	0.03300	0.08000	0.09100	0.11000	0.11400
Winter	0.01800	0.05600	0.07200	0.08400	0.09600

Table 1: Electric utility rates in $/kWh under the standard schedule (City of Austin, 2015a)

Under the time of use schedule, the tariff is further specified by weekday and time of day as seen in Table 2. The constant component of $0.05107 remains the same.

Season	Peak	0 - 500	501 - 1000	1001 - 1500	1501 - 2500	>2500
Summer (Jun – Sep)	On-peak (2-7PM, Mon-Fri)	0.09761	0.11003	0.12196	0.13031	0.14979
	Mid-peak	0.05040	0.06218	0.07134	0.07934	0.09512
	Off-peak (10PM – 6AM)	0.00493	0.01188	0.02182	0.02679	0.06158
Winter	Mid-peak	0.01201	0.03673	0.04891	0.06282	0.09761
	Off-peak (10PM – 6AM)	-0.00924	-0.00427	-0.00014	0.00692	0.04170

Table 2: Electric utility rates in $/kWh under the time-of-use schedule (City of Austin, 2015a).

3.4 Bootstrapping

By calculating the NPV for the original dataset we are attempting to make an estimate of the NPV of similar cooperatives in the population at large. However, there is no way to judge how accurate this estimate is and how it might have varied for other samples one could potentially encounter. One approach to dealing with this is bootstrap resampling, which was pioneered by Efron (1979). By resampling from the existing dataset, and calculating the statistic of interest for each resample, a set of values is obtained. The empirical distribution of those values is then taken as an estimate of the true sampling distribution (Dixon, 2001). In essence, bootstrapping allows one to compute estimates of uncertainty for a statistic, without knowing or assuming anything about the distribution of the underlying population (beyond the fact that it produced the sample in question).

For time-series data, bootstrapping requires additional consideration, since the data exhibits a temporal dependency. In other words, the observations of a variable are dependent on previous values of the same variable. As the Pecan Street dataset is hierarchically structured, it is possible to do nonparametric case resampling of independent households while leaving the underlying temporal structure of the observations intact. From the vector of unique household IDs in the original dataset $\boldsymbol{H}$ with length 128, a sample of the same length $\boldsymbol{H_b}$ is drawn with replacement. Following this, a new dataset is created by concatenating all associated observations for each household ID in $\boldsymbol{H_b}$. As this process results in duplicate household IDs, new numerical IDs are generated to tell the households apart. The NPV, or other statistic of interest, is subsequently computed for the new dataset. This process is repeated a number of times, which allows to construct an estimate of uncertainty for the value of the statistic.

Different recommendations are made in literature concerning the number of bootstrap iterations necessary. To minimize power loss, Davidson & MacKinnon (2000) suggest at least 399 iterations for a test at the .05 confidence level. For constructing confidence intervals, between 654 and 854 iterations are recommended by Andrews & Buchinsky (2000) for normally distributed errors. A similar result was obtained by Booth & Sarkar (1998), who cite 800 iterations required to minimize Monte Carlo error. Finally, Efron & Tibshirani (1986) advice a minimum of 1000 replications. There is no upper limit to the amount of bootstrap iterations to perform; more is better, although diminishing returns apply. However, since both the bootstrapping procedure and the subsequent forecasting are computationally expensive for the Pecan Street dataset due to the large amount of observations, 1000 iterations were performed for each condition to be compared. This meets the highest recommended minimum in literature, which comes recommended by the original author of the method, yet can be calculated in a reasonable time.

3.5 Time Series Forecasting

The historical Pecan Street dataset (and thus the bootstrapped resamples), when filtered as described in section 3.2, only contain 2 years of hourly observations. To calculate the net present value with a time horizon of 25 years, the historical results need to be extrapolated 23 years into the future. In other literature, uniform yearly returns were assumed for the purpose of long-term forecasts of microgrids (Y.-H. Chen, Lu, Chang, Lee, & Hu, 2012; Rangarajan & Guggenberger, 2011). However, the Pecan Street project has an extraordinary volume of data available, compared to previous research in this area. Consequently, it ought to be possible to achieve better results using modern time series forecasting models, which allow to capture both complex seasonal patterns and long-term trends.

For the implementation of the time series forecasting algorithms, the R package **forecast** was used (Hyndman & Khandakar, 2008; Hyndman, 2016). It provides convenient interfaces for the most common forecasting methods, as well as related utility functions. However, the defining feature of the package is the automated parameter tuning. As the forecast models are to be applied to each of the 1000 bootstrapped resamples, manually selecting all model parameters is not feasible. Instead, **forecast** compares several model variations internally and selects the best performing option according to Akaike's information criterion (AIC). The AIC is well-established as a way to compare goodness of fit between candidate models of the same class, while avoiding overfitting through penalizing model complexity (Bozdogan, 1987).

The dataset used for this paper presented a unique challenge due to its high seasonal frequency of 8766. The most commonly used model classes, exponential smoothing (ETS) and autoregressive integrated moving average (ARIMA), do not allow such high seasonal frequency due to computation constraints. One approach to handle this is to combine the ETS and ARIMA methods with a seasonal and trend decomposition using Loess (STL), as introduced by Cleveland, Cleveland, McRae, & Terpenning (1990). Another approach is using model classes that are able to handle high frequency data by default, such as TBATS (De Livera, Hyndman, & Snyder, 2011) or neural networks. As part of the model selection process, both options were considered.

The final forecast model was subject to three selection criteria:

- Forecast accuracy: how well does the model predict on holdout data?
- Compute time: how long does it take to fit the model to data and generate forecasts?
- Visual evaluation: how well does the model capture the apparent temporal pattern in the data?

To access forecast accuracy, the models were fit to data from 2013 and 2014; afterwards the mean absolute scaled error (MASE) was calculated for data from 2015. The mean absolute scaled error was chosen as a measure of accuracy, due to being suitable for time series containing zero values. The time to fit the model and forecast two seasonal periods was measured to determine the compute time. As the model would have to be refitted to each bootstrap resample, a cutoff of

	STL + Naïve w. drift	STL + ARIMA	STL + ETS	TBATS	Neural Network
Forecast accuracy	1.2622369	1.1972569	1.2419793	0.3655600	1.3941295
Compute time	100 ms	2400 ms	470 ms	161670 ms	204560 ms
Visual evaluation	Fail	Pass	Pass	Fail	Fail

Table 3: A comparison of the candidate models.

10 seconds was set for this criterion. As for visual evaluation, the forecasted periods were plotted side by side with the historical data, as seen in Figure 3.

The model scores for the three criteria defined above can be seen in Table 3. The TBATS model achieved the lowest MASE amongst the contenders, followed by the STL + ARIMA model. However, both TBATS and the neural network were too computationally expensive, taking respectively 16 times and 20 times longer than acceptable. On the visual evaluation, neither TBATS nor the neural network captured the right temporal pattern. The STL + Naïve model came close, but captured a highly implausible long term trend. The ETS and ARIMA models passed the visual evaluation, as the forecasts from both are usable with only minor adjustments. Based on the above, the STL + ARIMA model class was chosen for forecasting.

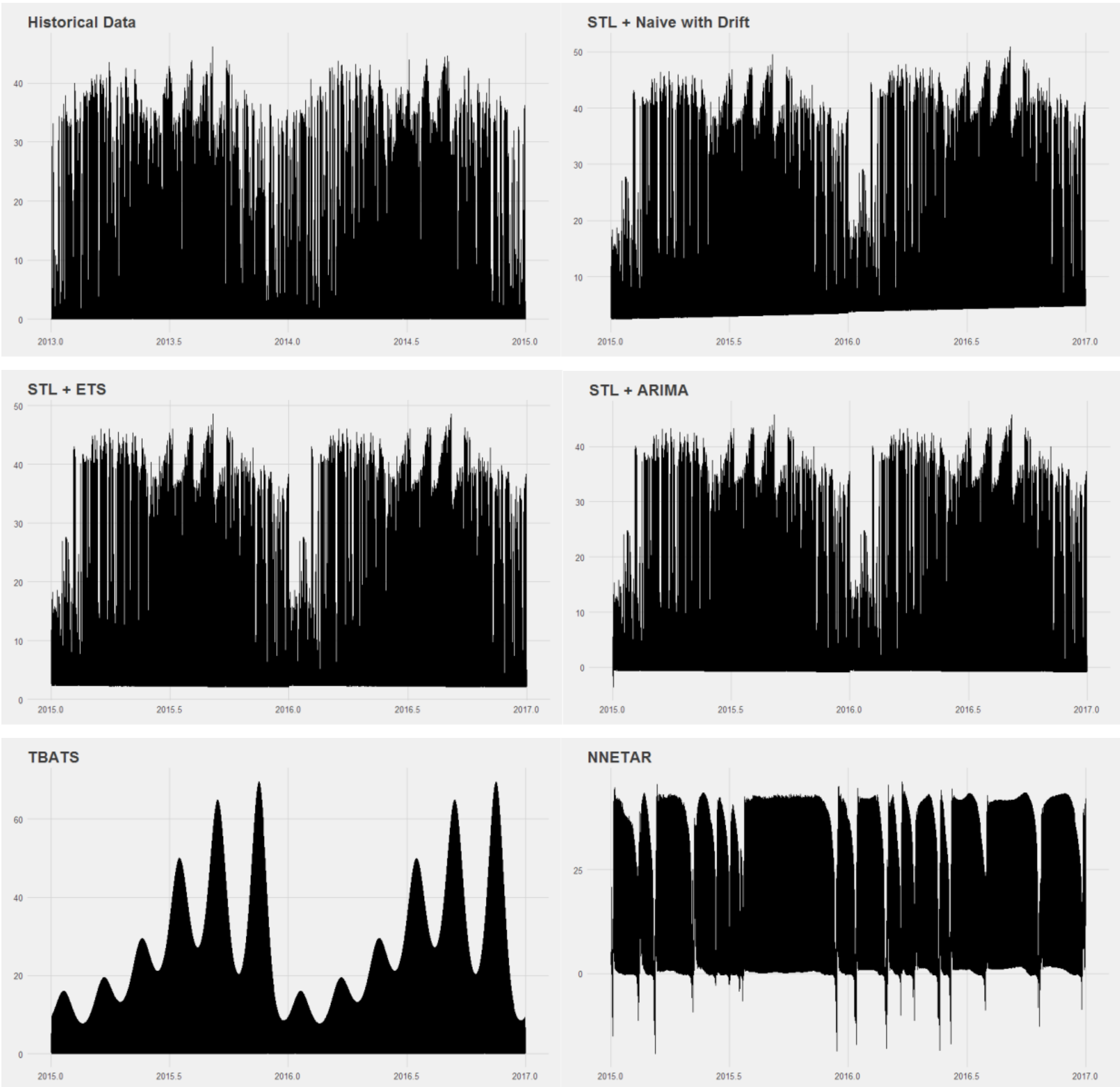

Figure 3: Two forecasted periods from the candidate models compared to the historical data (top left)

While the chosen algorithm performs best out of the evaluated candidates, sometimes the wrong model is selected. To prevent this, several bounds are imposed on the forecasted values automatically. In particular, the forecasted benefits cannot be negative, or have a trend that is too strong (i.e. quadratic).

4 RESULTS

In this chapter, the procedures described in the previous chapter are applied to the dataset. The results of the analysis are presented and elaborated upon.

4.1 VALUE AND PAYBACK PERIOD OF COOPERATIVES

Both the cooperative and individual benefits calculations outlined in section 3.3 are applied to the final filtered dataset of 128 households. Summary statistics for the values of use, gen and grid are provided in Table 4. Figure 5 displays density plots as well as pairwise scatterplots and correlation coefficients for the independent and calculated values. Initially, the standard rate structure is applied for the calculations. The resulting patterns are visualized (Figure 4) to study the difference between the alternatives. The patterns also serve as the input observations for the subsequent time series modeling procedure.

n = 128	Mean	SD	Median	Min	Max	Range	Skew	Kurtosis
datetime				26/12/2013 00:00	26/12/2015 23:00	2 years		
use	1.37	1.33	0.89	0.0	21.27	21.27	2.29	7.95
gen	0.80	1.29	0.00	0.0	10.61	10.61	1.72	2.46
grid	0.61	1.71	0.57	-7.5	21.20	28.70	0.40	3.33

Table 4: Descriptive statistics of the historical observations

It is readily apparent that the cooperative outperforms the sum of the individual households throughout the year. The differences are larger in the summer, when electricity consumption for air conditioning rises, along with the utility rates. This can be explained as a result of the interaction between the utility tariffs and feed-in rates. By operating as a cooperative, the households essentially maximize their collective savings from avoided grid electricity purchases. The above is achieved by sharing their surplus electricity with others who currently operate at a deficit. Under the individual scenario, surplus energy is always sold to the grid, with no sharing taking place. Under the standard utility rate structure, the utility rate is higher than the feed-in rate for all but the lowest usage tiers. Thus the cooperative scenario is more advantageous, given similar utility to feed-in rate proportions. This is reflected in the estimated financial metrics (Table 5): the cooperative has an NPV of \$ 1388 643, a payback period of 4.72 years and an IRR of 24.03%, compared to \$ 822 749, 6.64 years, and 16.37% respectively for the individual operation scenario.

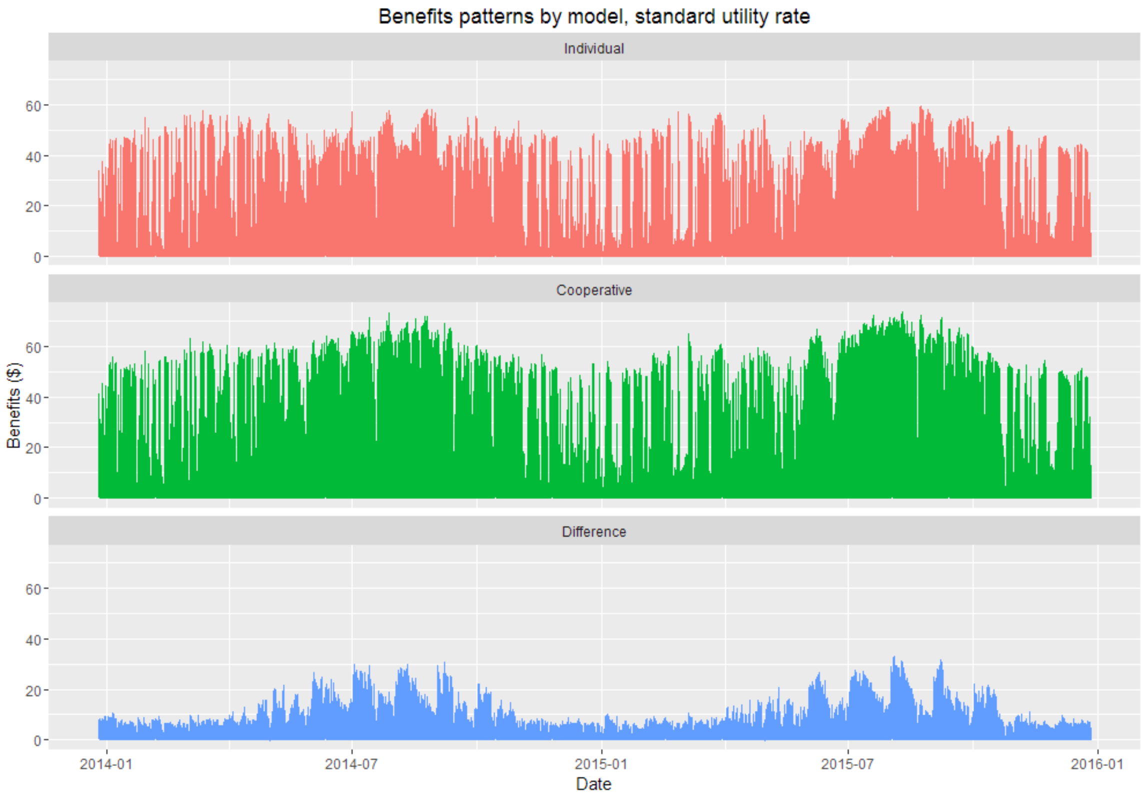

Figure 4. Individual and cooperative benefits patterns for the same time period. The bottom graph shows the (subtracted) difference between the two.

Having established that the cooperative scenario is likely to outperform the individual households, an attempt to quantify the magnitude of the difference is made. As this depends on the aggregate production and consumption patterns of the 128 households, the sample data can only provide a point estimate. To establish a confidence interval, 1000 samples with replacement are drawn from the original dataset (as described in section 3.4). Then, the STL + ARIMA forecasting algorithm is applied to each of the samples to project future cash flows. The resulting sample distribution is used to obtain bootstrap percentile intervals for the NPV, payback period and IRR. These intervals can be written as:

$$(1-\alpha)CI \text{ for } \theta = (\theta^*_{(\alpha/2)}\ ;\ \theta^*_{(1-\alpha/2)}) \tag{13}$$

Here, $\boldsymbol{\theta^*}$ refers to the bootstrapped values of the parameter of interest, while $\boldsymbol{\alpha/2}$ and $\boldsymbol{1\text{-}\ \alpha/2}$ are the 2.5th and 97.5th percentiles, respectively (for $\alpha = 0.05$).

The resulting bootstrap samples had an installed solar PV capacity of [673, 743] kWh peak, which corresponds to an initial investment cost of $ [549 517, 606 240] (the reported values are 95% confidence intervals). After forecasting, all future cash flows are discounted at a rate of 6%.

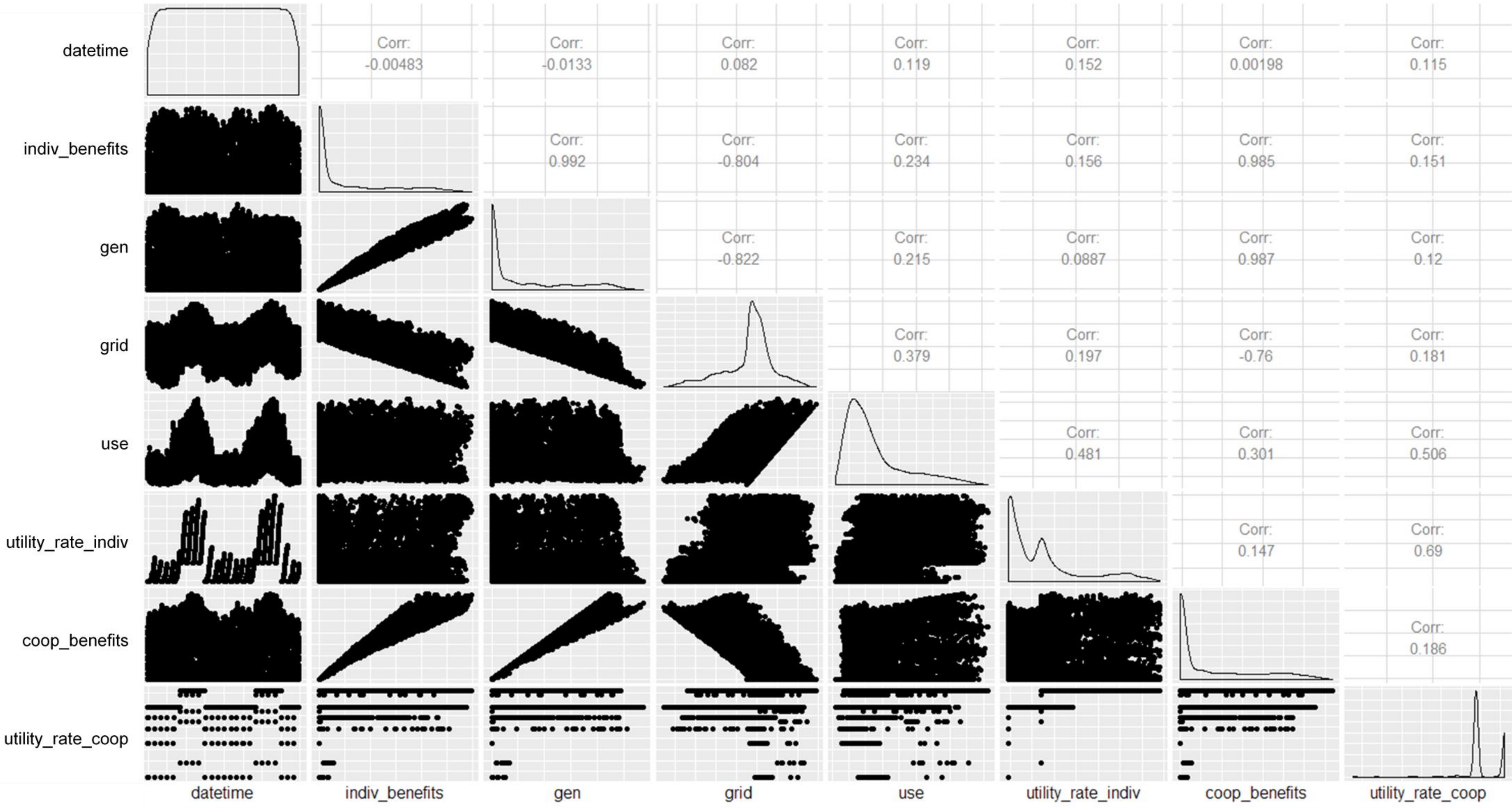

Figure 5: Histograms, density plots and correlation coefficients for use, gen, grid and the calculated variables.

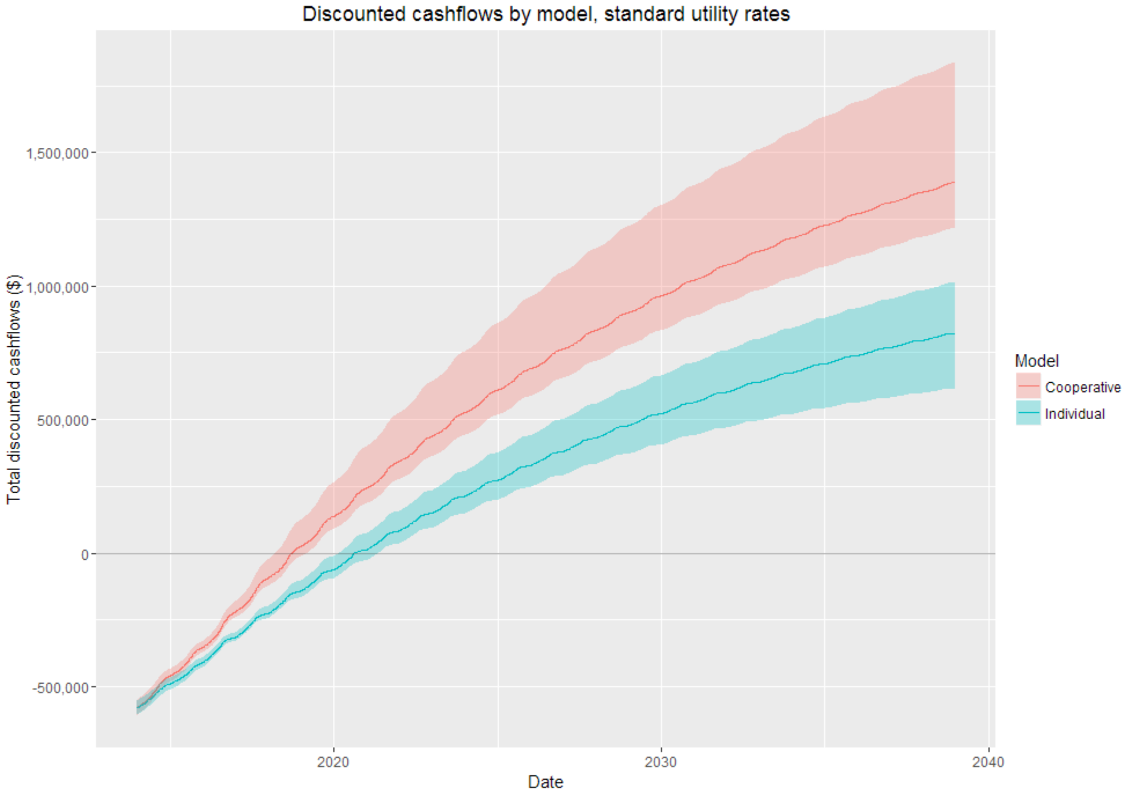

Figure 6: The cash flows of the two scenarios over time with 95% bootstrapped confidence intervals.

Under the standard utility rate scenario, this results in a substantial advantage for the cooperative over time, as can be seen in Figure 6.

One notable detail that can be seen from the plotted cash flows is the biased confidence interval of the cooperative scenario. If the original sample resembles the population, this could mean that the point estimate value is heavily influenced by outliers. Thus, the cooperative scenario is likely to perform better than the sample in reality.

The point estimates and bootstrapped 95% confidence intervals of the three financial metrics used to access the value of both scenarios are displayed in Table 5. The margin between the NPV confidence intervals under both scenarios is the added value the cooperative provides. As long as the present value of the additional costs to establish and run the cooperative do not surpass this margin, it can be said with 95% confidence that the cooperative is more profitable than the individual operation scenario for any given group of households. The difference between the upper bound of the individual scenario and the lower bound of the cooperative scenario in this case is $ 204494. Thus, as long as the present value (at a 6% discount rate) of the additional investment and maintenance costs necessary for a solar PV cooperative as described in this paper is less than $ 204 494, it can be concluded with 95% confidence that the cooperative is more profitable compared to individual solar PV operation. Additionally, it can be seen that the difference between the payback periods and IRRs of the alternatives is statistically significant at the 5% level.

4.2 Difference Between Rate Structures

The analysis from the previous section is repeated by applying the optional time-of-use utility rate structure in the benefits calculation, as opposed to the standard structure. While the standard structure only changes based on the season, the time-of-use structure also changes based on peak demand periods. On average the rates under time-of-use structure is cheaper, although the peaks during the summer are higher (see Figure 7). Again, how exactly this impacts the cash flow of the collective is dependent on the underlying consumption and production patterns.

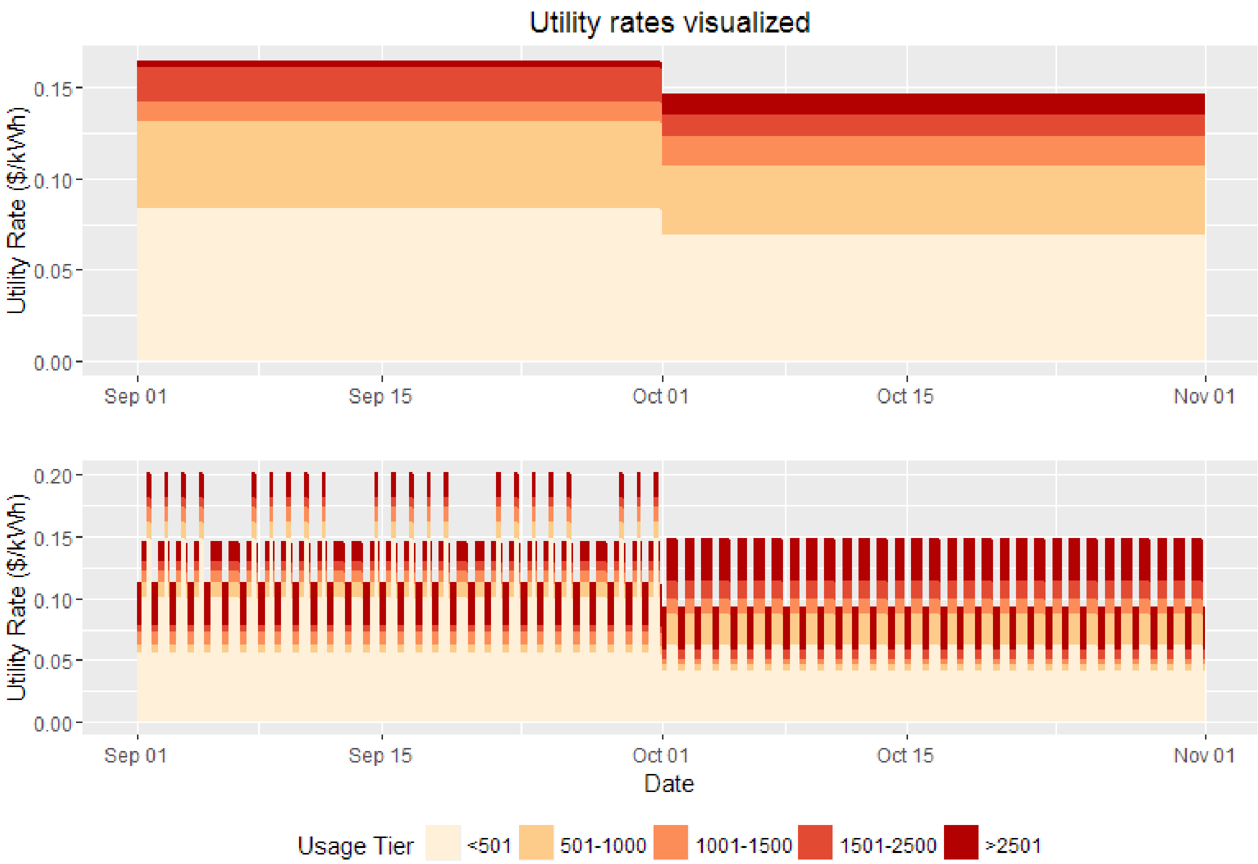

Figure 7: Utility rate ($/kWh) by usage tier. Top: standard structure, bottom: time-of-use structure.

However, in general one can expect the individual scenario to be more heavily impacted by the time-of-use rates, as there is more grid electricity used in that case. Furthermore, it can be seen in table 2 that the on-peak time-of-use periods take place during daytime, when the output from solar PV is highest. As cooperative members are likely to work during the day, the electricity consumption from those that are home is likely compensated by the high solar PV electricity generation. Under the individual scenario this is not an option, and any resulting deficit during on-peak hours will have a high impact. On the other hand, the lower utility rates paid during winter are advantageous for the relative profitability of the individual scenario. The effects mentioned above are made apparent in figure 7. During the winter months both scenarios benefit from the lower time-of-use rates. The differences fluctuate wildly during the summer, depending on whether there is an electricity deficit or not.

For the original dataset, the differences in the financial metrics are smaller than they were under the standard rate schedule. In this case the cooperative achieves a NPV of \$ 1277917, a payback period of 5.02 years and an IRR of 22.73%, while the individual scenario results in values of \$ 803 776, 6.85 years, and 16.19 respectively. It appears that the cooperative scenario is more heavily influenced by the different rate schedules than the individual is.

Figure 8: Subtracted differences between rate schedules by model. The start of summer is easy to see by the sudden emergence of negative values.

After applying the bootstrap procedure, the margin between the NPV intervals has increased. In this case, the minimum difference is $ 252 113. It can thus be stated with 95% confidence that under the time-of-use rate schedule, the solar PV cooperative will be more profitable than individual operation, provided the present value of additional costs does not exceed this value. Furthermore, with both the individual and the cooperative scenario's, the resulting confidence intervals for the NPV and IRR get more narrow under the time-of-use rates compared to the standard rates. This suggests that the benefits obtained under a time-of-use rate schedule do not vary as heavily with the cooperative members' consumption and generation patterns. However, the confidence intervals overlap between the rate structures for both scenarios studied. Therefore, it cannot be concluded that the average value of a cooperative in the population will be significantly different depending on the utility rate structure.

	NPV ($)		**Payback Period (years)**		**IRR (%)**	
	Est.	**95% CI**	**Est.**	**95% CI**	**Est.**	**95% CI**
Individual + standard	822749	[614177, 1011669]	6.64	[6.17, 7.36]	16.37	[14.04, 18.94]
Individual + time-of-use	803776	[628283, 839537]	6.85	[6.69, 7.87]	16.19	[13.53,16.95]
Cooperative + standard	1388643	[1216063, 1835522]	4.72	[4.24,5.20]	24.03	[21.83,28.78]
Cooperative + time-of-use	1277917	[1091649, 1556627]	5.02	[4.55,5.43]	22.73	[20.42,26.00]

Table 5: The parameters of interest under both scenario's and for both rate structures.

4.3 Smart Thermostats

Next, the effect of smart thermostats is investigated. As mentioned in the last chapter, the dataset contains households which have at least one Nest smart thermostat installed, and those that have none. For both groups, the observations from corresponding households are extracted into a subset for use in the calculations. As the households and their number in both the subsets are different, comparing their NPV is not possible. However, the payback period and IRR are both inherently proportional to the initial investment and can be used for this purpose. The calculations are performed for the cooperative scenario and under the standard rate schedule. Descriptive statistics for both groups can be found in Table 6.

	Mean	SD	Median	Min	Max	Range	Skew	Kurtosis
				0 Nests (n = 110)				
use	1.36	1.32	0.89	0.0	21.27	21.27	2.33	8.42
gen	0.81	1.29	0.00	0.0	10.61	10.61	1.72	2.46
grid	0.58	1.71	0.57	-7.5	21.20	28.70	0.40	3.33
				1+ Nests (n = 18)				
use	1.43	1.43	0.89	0.0	13.18	13.18	2.09	5.63
gen	0.74	1.24	0.00	0.0	7.92	7.92	1.88	3.10
grid	0.77	1.78	0.59	-5.82	13.18	18.99	0.74	3.17

Table 6: Descriptive statistics of the historical observations for both groups

The results from the estimation and bootstrapping procedure are displayed above in Table 7. No significant difference in IRR or payback period could be found. This means that, while there may be differences in consumption patterns between the groups, it can be concluded with 95% confidence that these differences are not sufficient to significantly impact the payback period and IRR. Furthermore, the intervals overlap with the overall cooperative + standard schedule intervals in Table 5.

	Payback Period (years)		**IRR (%)**	
	Est.	**95% CI**	**Est.**	**95% CI**
1 – 3 Nest thermostats	4.12	[4.25, 6.67]	29.57	[15.78, 29.57]
No nest thermostats	4.41	[4.26, 5.21]	28.48	[21.80, 28.49]

Table 7: The parameters of interest for both groups under the standard rate structure.

4.4 Feed-in Rate Analysis

The relative profitability of a solar PV cooperative is fully determined by the feed-in rate, that is, the rate at which generated surplus electricity can be sold back to the grid operator. If this rate is zero, a solar cooperative will always be more profitable than individual operation, as it purchases less grid electricity. Conversely, if this rate surpasses the average grid electric rate paid by the members, individual operation is superior from a financial standpoint. This relationship is linear, but the strength of it is dependent on the cooperative members and their combined generation and consumption patterns.

To determine the influence of the feed-in rate, the feed-in rate is manually varied with steps of one cent. For each new rate, the benefits are recalculated for the historical observations, and the

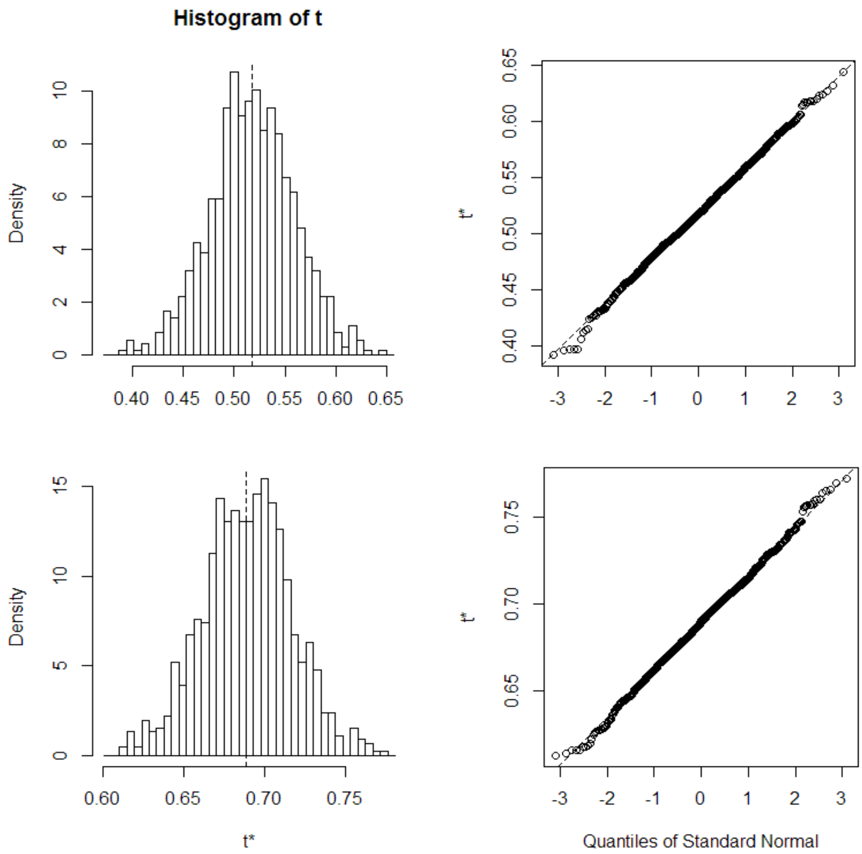

Figure 9: Histograms and Q-Q plots for the linear model coefficients. Top pair shows the cooperative scenario; bottom pair shows the individual.

average annual return rate as a percentage of the initial investment is obtained. No time series forecasting is done as part of this analysis. A linear regression model is then fitted on the value-pairs, and the resulting coefficients are recorded. Subsequently, the above process is repeated for all bootstrap replications, under both individual and cooperative scenarios, to obtain a suitable 95% confidence interval. Results appear in Table 8.

Histograms and Q-Q plots for the bootstrapped slope coefficients are displayed in Figure 9. The model coefficients appear close to normally distributed under both scenarios, which bodes well for the coverage of the confidence intervals.

	Intercept		Slope	
	Est.	**95% CI**	**Est.**	**95% CI**
Cooperative scenario	0.1500715	[0.1408, 0.1592]	0.5182665	[0.4364, 0.5971]
Individual scenario	0.0791854	[0.0726, 0.0856]	0.6885305	[0.6330, 0.7421]

Table 8: Model coefficients and confidence intervals for the linear regression of historical annual percentage returns against the feed-in rate.

The obtained intervals indicate that with no feed-in rate, a renewable solar PV cooperative as described here would achieve yearly returns between 14.08% and 15.92%. Operating individually these households would obtain average yearly returns between 7.26% and 8.56%. With every cent increase in the feed-in rate, the yearly return is likely to grow between 0.4364% and 0.5971% for the cooperative scenario, and between 0.6330% and 0.7421% for the individual mode of operation. Finally, by solving for *x* the crossover point can be determined at which, all else being equal, the individual scenario will surpass the cooperative in terms of yearly returns. Algebraically, it can be shown that this will occur at a feed-in rate situated on the interval [0.1805, 2.4122]. Thus, it is possible to conclude with 95% confidence that, all else being equal, a solar PV cooperative will remain more profitable than individual operation for all feed-in rates under $ 0.1805. For comparison, the nominal feed-in rate used for the calculations in this chapter is $ 0.1090. A graphical representation of the obtained equations and confidence intervals can be seen in Figure 10.

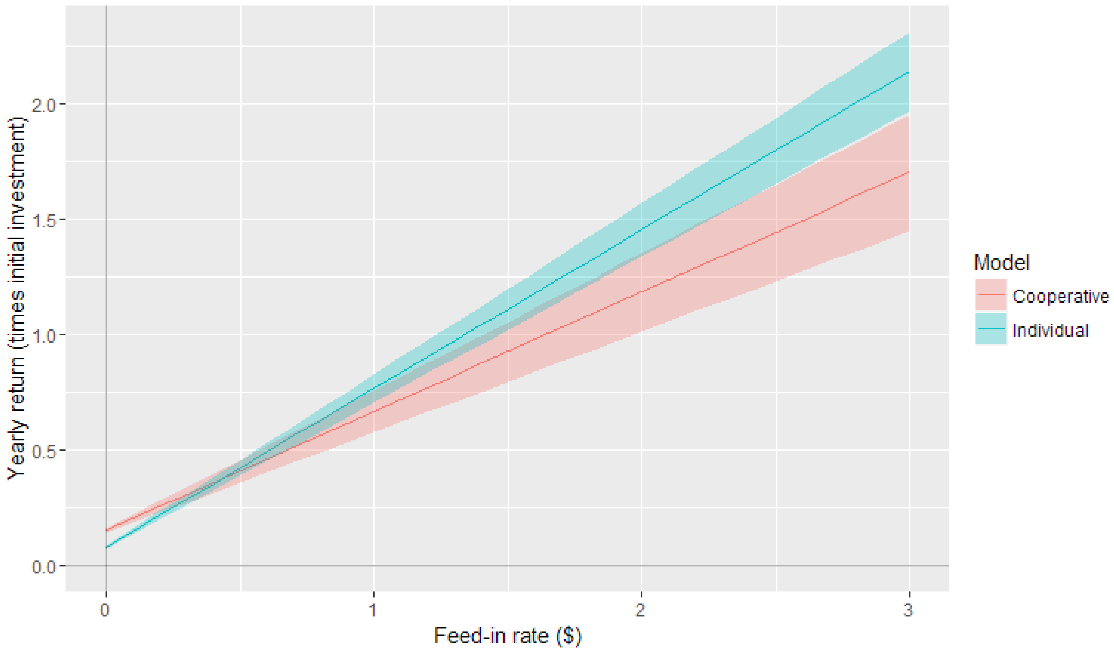

Figure 10: A plot of the obtained linear regression equations with confidence intervals.

5 Conclusions & Recommendations

This chapter answers the research questions using the results presented above and discusses them in the context of the theoretic framework from chapter 2, along with relevant assumptions. Finally, recommendations for future research are provided.

5.1 Conclusions

In this paper, an attempt is made to quantify the value of renewable energy cooperatives, both in absolute terms as an investment opportunity, and in relative terms when compared to the next-best alternative of individual renewable energy investment. The scenario investigated is that of a renewable energy cooperative defined as a grid-connected microgrid consisting of:

- 128 different consumer households,
- Distributed generation provided by solar PV panels installed on each of the houses, for a total installed capacity between 673 and 743 kW peak,
- Some form of short term distributed storage capacity to provide load balancing and the ability to share energy between households (no long term energy storage was assumed to be present),
- The other components required for microgrid operation, including a grid interconnect and control systems (Kroposki et al., 2008)

Data used in the analysis consists of several years of electricity generation and usage measurements for each of the households, at hourly intervals. To the authors best knowledge, no financial simulation of a renewable energy cooperative or microgrid has been published based on a comparable volume of data. The simulations are performed using a combination of bootstrap resampling and time series forecasting techniques, and appropriate 95% confidence intervals are used to answer the research questions. The next-best alternative being compared against is defined as the same set of households operating their solar PV installations individually.

5.1.1 RESEARCH QUESTIONS (1), (2)

The main research questions concerned the NPV, discounted payback period and IRR of the cooperative. According to the results obtained, the NPV of such a cooperative is found to be within the interval of $ [1 216 063, 1 835 522] based on a 25-year time horizon. The cooperative recovers its investment cost within the interval of [4.24, 5.20] years, with a corresponding yearly IRR between [21.83, 28,78] percent.

In comparison with the alternative individual scenario, the difference in net present value is between $ [204 494, 1 221 345], in favor of the cooperative. The lower bound of the last interval can be seen as the maximum level of the distributed storage and other microgrid component costs, as well as any other investment costs, at which the cooperative is more profitable than the alternative. In terms of the payback period and IRR, the differences in favor of the cooperative are found to be [-0.97, -3.12] years and [2.89, 14.74] percent respectively.

If the initial sample indeed resembles the population, then a renewable energy cooperative as described here does add value compared to individual solar panel operation (subject to the comments in section 5.1.5), based on the benefits reduced grid purchases and electricity sales alone. Furthermore, it is also able to fulfill the other benefit functions as outlined by Morris, Abbey, Joos, & Marnay (2011). Thus, the resulting added value may be even higher, especially if positive externalities are taken into account.

Moreover, even if a renewable energy cooperative was close in financial value to the individual scenario, it would still likely be perceived as the preferable option by its potential members, as survey results from Sagebiel, Müller and Rommel (2014) suggest. Trust and control, which are identified as major issues for cooperative in section 2.3.3, are not much of a concern here, considering the operational logic of the microgrid is fully automated. And the larger bargaining power afforded by the cooperative organization potentially allows economies of scale on the financing and purchasing sides.

5.1.2 SUB-QUESTION (A)

Effect of time-of-use utility rates were investigated as part of research sub-question (a). Under the time-of-use rates, the obtained intervals are narrower than under the standard rates. Consequently, the minimum margin in favor of the cooperative grows, with the upper bound for additional investment now being $ 251 113, which amounts to 22 % higher. However, the intervals for the financial metrics all overlap with the standard rates case. And thus, it cannot be concluded that either of the scenarios is likely to perform significantly better or worse under the time-of-use rates on average.

The narrowing confidence intervals suggest that even if the cooperative does not necessarily profit from the time-of-use utility rates, they may still be preferable from the perspective of the utility. This is due to the fact that a more even expected cashflow allows for reduced risk in operational, strategic and financing decisions for the latter.

5.1.3 SUB-QUESTION (B)

As smart thermostats are reported to result in lower cooling energy consumption, their effects on the payback period and return rate were investigated as part of sub-question (b). Based on accompanying metadata of the Pecan Street dataset, it is split into two subsamples, based on the reported presence of at least 1 Nest thermostat. However, no significant difference could be found between these groups in the financial metrics at the 95% confidence level; furthermore, both overlap with the intervals from question (1).

This answer does not necessarily mean that the Nest thermostats have no effect on the payback period and return rate. Instead, it means that the scale of these effects, if any, is too small to be picked up by the forecasting procedure employed. One of the studies performed by Nest (Nest Labs, 2015) cites electricity savings of 429 kWh/year. In comparison, the lower bound in this study for the installed capacity of the total cooperative is 673 kWh. This means that the energy production of the cooperative can potentially surpass the total electricity savings for one thermostat in a single hour. Consequently, the thermostats might still have a positive effect from the perspective of individual cooperative members.

5.1.4 SUB-QUESTION (C)

The cooperative scenario minimizes grid electricity purchases, which results in lower sales of electricity back to the utility. Consequently, it follows that the feed-in rate directly influences both the absolute yearly return percentage and the difference relative to the individual scenario. For sub-question (c), the strength of this relationship is determined through a bootstrapped regression analysis. Confidence intervals for the linear regression coefficients $\boldsymbol{\beta_0}$ and $\boldsymbol{\beta_1}$ are calculated; they equal ([0.1408, 0.1592], [0.4364, 0.5971]) for the cooperative scenario, and ([0.0726, 0.0856], [0.6330, 0.7421]) for the individual. Solving for the minimum intercept of the resulting linear equations, it can be concluded with 95% confidence that a cooperative will, on average, be more profitable than the alternative scenario for all feed-in rates below $ 0.1805. This would represent a 60% increase over the nominal feed-in rate of $ 0.1090 used for all preceding calculations.

To put the feed-in rate further in context, Couture & Cory (2009) provide an overview of feed-in rate policies across 6 states in the US. Only in one state (Florida) the resulting feed-in rate over 25 years is higher than under the conditions studied. In the other states examined, the duration of the feed-in rate is shorter, the project size is limited and/or the rate is lower, resulting in a lower average over the 25-year duration. This suggests that the feed-in rate that was studied is more likely to be biased downwards rather than upwards; and thus, the relative increase in value from the cooperative is more likely to be higher, assuming the linear model holds.

5.2 Discussion

Financial results obtained depend heavily on estimates, and are influenced by regional differences as well. Thus, some remarks are in order on the likelihood of these results.

5.2.1 Installed Cost and Price of Solar PV

The installed price for solar PV systems in the Pecan Street project was subsidized at around 84% through rebates from various sources. At the average installed price of $ 5.1 per W of peak capacity that was used in the calculations (Feldman et al., 2013), the average rebate received translates to a discount of $ 4.284 per W peak. Initially, this number may appear somewhat unrealistic, and indeed it may be somewhat distorted, since particular solar PV configurations were more highly incentivized than others (Pecan Street Smart Grid Demonstration Project, 2015). However, the value is not all that unlikely for panels installed in 2013 in the US, when taking literature findings into account.

The average total after-tax incentive for residential solar PV found by Barbose, Darghouth, Wiser, & Seel (2011) was $ 3.2 per W peak in 2010. While these incentives are legislated to decline over time, the installed prices per W peak are dropping as well. In particular, a follow-up report found a median installed price of $ 4.2 per W peak for residential systems in the US (Barbose et al., 2015). If the cooperative is able to achieve similar negotiating power as a comparable commercial system in the range of 500-1000 kW, the median installed price is even lower at $ 2.9 per W peak.

All of the above considered, there is little reason to believe that the installed cost of the solar PV systems would be much higher on average in the US. The results obtained are relatively robust to changes in the installed cost as well: the cooperative achieves a positive NPV (with 95% confidence) for installed costs up to 3.01 times higher than estimated, ceteris paribus.

5.2.2 *NEXT BEST ALTERNATIVE SCENARIO*

The relative value compared to the next best individual alternative heavily depends on the cost of the microgrid components. Very few cost estimations of these components can be found, especially for microgrids without long-term distributed storage. Somewhat comparable numbers are cited by Costa & Matos (2006) and Morris et al. (2011), who took $ 77 700 and $ 129 000 in additional component cost, respectively. These values fall well within the margin of profitability established in question (1).

5.2.3 *MICROGRID CONTROL SYSTEMS*

The cooperative microgrid, as described mathematically in chapter 3, operates on a very naïve static dispatch logic: it always prioritizes minimizing total grid purchases. This is demonstrably suboptimal if the current utility rate can be below the feed-in rate depending on the time period. In-depth examination of more advanced microgrid control algorithms has been performed by multiple authors (C. Chen et al., 2011; Liu et al., 2011). Their results suggest that, given a less simplistic algorithm, the added value of the cooperative is likely to be higher.

5.2.4 *DIFFICULTIES IN COMPARISON ACROSS REGIONS*

The obtained results should be a good approximation for solar PV cooperatives in the southern US. However, in other markets and other regions across the globe, many independent variables change simultaneously. For comparison, a short description of the relevant differences between the US and Europe is provided:

- The yearly total output of a 1 kW peak solar PV system varies between 600 and 1500 kWh across Europe due to differences in climate (Šúri, Huld, Dunlop, & Ossenbrink, 2007).

- Energy consumption patterns are likely to differ as well, with one example being the rarity of air-conditioning in residential buildings for most of Europe.
- Grid electricity rates range between € 0.096/kWh for Bulgaria and € 0.305/kWh for Denmark (Eurostat, 2016).
- European government incentives for solar PV energy are structured differently, with less focus for upfront rebates but higher feed-in rates in general (Campoccia, Dusonchet, Telaretti, & Zizzo, 2009).
- Solar PV system installed prices in the US are higher compared to many other markets (Barbose et al., 2015).

It is thus extremely challenging to generalize the absolute NPV, payback period and IRR for other regions. However, a renewable cooperative is likely to outperform the next best alternative, as long as the feed-in rate is not much higher than the average utility rate. Given that high feed-in rates are meant as a temporary incentive, the feed-in rate as studied may be a good representation of the future.

5.3 Recommendations for Further Research

This paper aims to provide insight into the economic viability of renewable energy cooperatives, while addressing many concerns associated with them. In doing so, it addresses a notable gap in existing literature, as identified by Yildiz et al. (2015). As part of the conducted analysis, a simulation and forecasting framework is established that can be used to study various facets of renewable cooperatives and other microgrids based on a large volume of data.

Several areas of the base model could be built and extended upon by future studies. One opportunity in particular is the addition of a simple battery simulation to the model. This would allow to investigate the impact of long-term storage capacity on the profitability of this cooperative. The algorithm used to control the microgrid could also be improved further to make more optimal decisions on when to buy or sell electricity. With minor modifications, the model could also be used to study short-term effects; the result may also be used in actual microgrids for short-term forecasting purposes.

Other areas for further research do not require altering the developed model. For instance, the influence of demographic variables on the financial results is a potentially interesting subject to study. Further options include the addition of other renewable sources, an investigation into DSM techniques, or calculation of the positive externalities. One particular area that has been found sorely lacking in literature is the cost required to establish a microgrid. Given that they are likely to become more common in the future, it is important to have at least some estimates to go by.

Finally, the current model needs to be re-evaluated on datasets originating from different regions, and/or covering a longer time span. Therefore, continued attention and support for making data obtained from research projects such as Pecan Street publically accessible is of the utmost importance.

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