Aalto University
School of Business

SOLAR POTENTIAL IN HELSINKI

Optimizing the allocation of solar panels on the roofs of Helsinki

Master's Thesis
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Information and Service Management
Spring 2021

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Abstract of master's thesis

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Title of thesis Solar potential in Helsinki

Degree Master of Science in Economics and Business Administration

Degree programme Information and Service Management

Thesis advisor(s) Juuso Liesiö

Year of approval 2021 Number of pages 53 Language English

Abstract

Solar photovoltaics (PV) has seen increased global adoption and decreased costs in the latest decades. The increased adoption of solar power and other renewable energy sources has been associated with the stringent goals regarding the cutting of carbon emissions set forth by different countries and international organizations. The city of Helsinki as well has its own climate strategy, aiming to become carbon-neutral by 2035. Alongside other sources of renewable energy, solar power has become a viable alternative to the more pollution-intensive sources cost-wise in many regions of the world.

Still, solar power generation has some inherent challenges. Most importantly, due to the variance of solar irradiation, solar PV based power generation is variable over the time of day and year. Thus, any electricity grids incorporating solar panels must include power grid balancing measures. Moreover, the location of such systems is paramount when investments are considered, as the electricity potential varies across different geographies.

Spatial decision making, such as choosing the location of solar systems, often involves conflicting criteria and a multitude of potential alternatives. While methods and objectives vary, geographic information systems (GIS) are often used to support spatial decision making. As the locations of solar power installations are paramount to their efficiency, spatial decision making combined with GIS has often been used in the literature concerning solar systems.

The aim of this study is to assess the potential of large-scale utilization of solar panels on the roofs of Helsinki, Finland. First, a literature review is conducted on the topics of solar power and spatial optimization. Secondly, a linear programming model is constructed with a goal of finding optimal combinations of roofs for various electricity generation target levels, while simultaneously minimizing the area taken. A dataset describing the roofs in Helsinki and their yearly total solar irradiation is used to test and validate the model. Finally, the costs associated with the optimal allocations are analyzed and discussed. While truly accurate forecast of costs can't be produced, the analysis may be used by policy makers for an initial assessment of the different methods to achieve the climate strategies of the city of Helsinki.

Keywords solar power, GIS, spatial optimization

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Maisterintutkinnon tutkielman tiivistelmä

Tekijä Juho Miettinen

Työn nimi Aurinkoenergian mahdollisuudet Helsingissä

Tutkinto Master of Science in Economics and Business Administration

Koulutusohjelma Information and Service Management

Työn ohjaaja(t) Juuso Liesiö

Hyväksymisvuosi 2021 Sivumäärä 53 Kieli englanti

Tiivistelmä

Aurinkoenergiaa hyödynnetään yhä enemmän ja sen kustannukset ympäri maailmaa ovat laskeneet viime vuosikymmenien aikana. Uusiutuvien ja vähäsaasteisten energiamuotojen kuten aurinkoenergian hyödyntäminen on lisääntynyt, kun eri maat ja kansainväliset organisaatiot ovat asettaneet kunnianhimoisia ilmastotavoitteita, luvaten vähentää päästöjä tai jopa pyrkiä päästöneutraalisuuteen. Myös Helsingin kaupungilla on oma ilmastostrategiansa, jossa tavoitellaan hiilineutraalisuutta vuoteen 2035 mennessä. Lisääntyneiden investointien myötä aurinkoenergia ja muut uusiutuvan energian muodot ovat paikoin jo kilpailukykyisempiä hintojen suhteen kuin perinteiset energiamuodot.

Aurinkoenergiaan liittyy kuitenkin joitakin haasteita. Auringonsäteilyn vaihtelu sekä päivänsisäisesti että vuodenaikojen mukaan johtaa luonnollisesti siihen, että aurinkopaneelien tuottama energia vaihtelee myös päivästä ja vuodenajasta toiseen. Aurinkoenergian sähköverkkoon lisäämisen myötä tulee verkkoon lisätä järjestelmiä, jotka tasapainottavat sähkökuorman vaihtelua. Myös aurinkoenergiajärjestelmien sijainti on keskeinen kysymys investointipäätöksissä, koska auringonsäteilyn vaihtelu on huomattavaa eri alueiden välillä.

Spatiaaliseen päätöksentekoon kuten aurinkojärjestelmien sijainnin määrittelemiseen liittyy usein monia vastakkaisia kriteerejä ja suuri joukko mahdollisia vaihtoehtoja. Vaikka päätöksenteon menetelmät ja tavoitteet vaihtelevat, sen tukena käytetään usein paikkatietojärjestelmiä (GIS). Koska aurinkoenergiajärjestelmien sijainti on erityisen tärkeä niiden tuottavuuden kannalta, aurinkoenergiaa käsittelevässä tutkimuskirjallisuudessa on usein hyödynnetty spatiaalisen päätöksenteon menetelmiä.

Tämän tutkimuksen tavoitteena on arvioida katoille sijoitettavien aurinkopaneelien hyödyntämisen potentiaalia Helsingissä. Tutkimusmuotoina toimivat sekä kirjallisuuskatsaus aurinkoenergiaan ja spatiaaliseen päätöksentekoon, että lineaarisen optimoinnin mallin luominen kattojen valintaan. Mallissa eri sähköntuoton tasoille muodostetaan optimoinnin avulla kattojen osajoukko, jonka vaatima pinta-ala minimoidaan. Mallin testaamisessa ja validoinnissa hyödynnetään tietoaineistoa Helsingin katoista ja niiden vuotuisista auringonsäteilykertymistä. Viimeiseksi arvioidaan kustannuksia, joita löydettyjen kattojen osajoukkojen käyttäminen aurinkoenergian tuottamiseen vaatisi. Vaikka täysin tarkkojen kustannusten arvioiminen ei ole mahdollista, suuntaa antavia viitearvoja voidaan käyttää hyväksi verratessa eri strategioita, joita Helsingin kaupungilla on käytössä sen pyrkiessä toteuttamaan ilmastostrategiaansa.

Avainsanat aurinkoenergia, GIS, spatiaalinen optimointi

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1 Introduction

In recent years, climate change and specifically the role of humans in it has become a focus both in political discourse and scientific research all over the world. Unsustainable consumption has led to increasing energy usage and carbon emissions. Developments in energy generation and infrastructure are needed to combat climate change and move societies towards more sustainable consumption. Because of the global nature of the challenge, inter- and multinational organizations play a key part in this endeavor.

A major international milestone in the fight against climate change was reached in 2015 with the adoption of the Paris Agreement by the parties of United Nations Framework Convention on Climate Change. The agreement entered into force on 4th of November 2016, and as of the writing of this thesis, 195 countries have signed the agreement while 189 of the signees have ratified it. (United Nations 2020).

The Paris Agreement (2015) outlines the collective effort of its parties to limit the 21st century's temperature rise to 2.0 C° from the pre-industrial levels, preferably to 1.5 C°. The participant countries are expected to, to the best of their ability, put forth actions towards the common goal through nationally determined contributions. The parties also need to report on their progress regularly, and their aim should be to incrementally increase their efforts moving forward.

On European level, the European Union aims to be the global leader towards a greener future. According to the European Green Deal, by 2030, the members of EU should collectively cut their emissions to 50% compared to the levels of 1990, and a net-neutrality of greenhouse emissions is to be reached by 2050. Important considerations include incentivizing green investments, policies guiding industry and consumer practices, increased energy efficiency across different sectors and sustainable mobility and transportation. (European Commission 2019a).

Finland, being an EU member and having ratified the Paris Agreement, has also policies and laws in place to combat climate change. The current climate law in Finland came into effect on 1st of June in 2015. It binds Finland to cut its emissions by 80% by 2050 compared to the levels of 1990. However, the current coalition led by prime minister Sanna Marin is currently revising the climate law so that Finland would reach carbon-neutrality by 2035. (Ympäristöministeriö 2020).

On a municipal setting, the city of Helsinki has already adopted a more ambitious climate strategy aiming to become carbon-neutral by 2035. Currently, over 50% of the emissions produced in Helsinki are from heating buildings, and further 15% are from general electricity usage. (Helsingin kaupunki 2018). While the emissions can be decreased by e.g. improving the heat retention of buildings or flat out decreasing general electricity usage, an important part of the city's strategy is a push towards renewable energy sources. One notable way of a large-scale utilization of renewable energy sources would be the increased adoption of solar power.

Solar power generation has leaped forward immensely in the last decade. While the world produced some 32 terawatt-hours (TWh) of solar photovoltaic energy in 2010, the amount produced in 2018 was already over 554 TWh (International Energy Agency 2020b.) Moreover, the International Energy Agency (IEA) (2020a) forecasts that solar photovoltaics generation will further increase its capacity by almost 700 gigawatts by 2024. At the same time, prices of photovoltaic modules have drastically decreased, nearly 90% since 2010, and electricity generated by photovoltaics has reached cost parity with wholesale market prices in California, China and parts of Europe (Financial Times 2019.)

In Finland, solar power has been utilized successfully for example by grocery stores (Kauppalehti 2018.) As they require a lot of energy for refrigeration especially in summer, they can efficiently use solar panels for leveraging the peak power generation during summer months. Still, other businesses and households are also increasingly installing solar power systems. Although solar installations have traditionally been used in cottages and individual houses, in Helsinki they are becoming more widespread on the roofs of schools, commercial properties and apartment buildings (Helsingin Sanomat 2020.)

For solar power to be viable in Helsinki, the location of the panels, the associated costs and power generation potential are of paramount importance. Thus, in this thesis I will specifically concentrate on the viability and cost-efficiency of solar energy on the roofs of Helsinki. My research problems are:

1. How should solar panels be allocated to the roofs of Helsinki to maximize their yield while minimizing the area required?

2. How cost-efficient is the optimized allocation compared to the current and future consumer electricity prices in Helsinki?

To answer the first research question, an optimization model is created with the goal of finding a group of roofs satisfying a given electricity production target while minimizing the required area. The model is then applied to an open spatial dataset created by Helsingin seudun ympäristöpalvelut (HSY 2015) to test and validate the model. To answer the second research question, the costs of the allocations obtained from the optimization model are estimated by using the offerings of a local solar panel provider. Combining the results from the two research questions should answer whether solar panels are a viable method of power generation on the roofs of Helsinki. Additionally, a literature review is performed to further give context and assess the viability of solar power in Helsinki.

The aim of my thesis is twofold. Firstly, my goal is to provide actionable information to the city of Helsinki regarding the potential of solar panel allocation on the roofs of the city. Moreover, the model created could be used on other similar projects as well to gauge potential allocations in other areas/cities. Depending on the cost-efficiency of solar panels compared to alternative sources of power generation and the average prices of electricity in Finland, the city of Helsinki could either use my research as a starting point for a larger scale solar panel adoption or focus on other, more viable, options. Secondly, I aim to provide a new case study in the field of spatial optimization and demonstrate a working use case for combining geographical information systems and (multi-objective) linear programming.

The structure of my thesis is as follows. Firstly, Sections 2 and 3 are dedicated to solar power and graphical information systems (GIS), respectively. I will conduct a literature review to highlight the changes surrounding these fields, as well as talk about notable implementations both in the literature and in practice. Moreover, the benefits and challenges inherent to solar power and spatial optimization are discussed. In Section 4, I will go through the modelling of the panel allocation problem. Furthermore, I will talk about the methods used in my thesis, and perhaps more importantly, why they were chosen. In Section 5, I will first discuss the data used with the model, and then the results of the optimization. Practical implications for both the city of Helsinki and individual citizens interested in solar panel adoption are discussed. Finally, Section 6 concludes my thesis by summarizing the key points of this study, as well as its implications for future research in the fields of spatial optimization and solar power utilization.

2 Solar power

Photovoltaic (PV) power generation, colloquially solar power, is based on the photovoltaic effect, i.e. a material's property of generating an electric current when exposed to the photons of solar radiation (light). Solar panels are then a set of connected photovoltaic cells in a circuit. Notably, in contrast to alternating current (AC) in most electric grids, solar panels generate direct current (DC). Thus, for appliances requiring AC, solar panel systems require an inverter, which can change DC into AC. An inverter is also needed if the owner of a solar system wants to connect the systems to the electric grid, for example to sell surplus electricity to others. (Motiva 2020).

However, solar PV panels are not the only method of utilizing sunlight. Solar irradiation can also be harnessed in via concentrated solar power (CSP) systems: using lenses and/or mirrors, sunlight is focused on a fluid which, once heated, is used in a heat engine to produce electricity (Jacobson & Delucchi 2011a.) While CSP plants are a viable method of solar power generation, they are left outside the scope of this thesis, instead the focus being on PV solar panels.

In this section, I will go through the results of the literature review concentrating on solar power. Topics include the history of the specific technology, its current real-life applications, and the benefits and challenges it may entail. The section is further divided into a global and Finnish perspective in Sections 2.1 and 2.2, respectively.

2.1 Solar power in the world

While solar power (and other renewable energy sources) has gained traction especially in the recent decades following the increasing awareness surrounding climate change, the technology is by no standards new. Already in 1881, the first solar panel based on selenium was created by Charles Fritts. Still, the invention was overshadowed by the creation of the first coal-based electricity plant by Thomas Edison. (CleanTechnica 2014).

Solar power has remained marginal compared to e.g. coal for much of its history, but some increase in utilization can be seen arising starting from the beginning of the 21st century. Figure 1 represents the changes in the quantity of electricity produced worldwide from different sources over time. The three most prevalent sources of renewable energy, hydro power, solar photovoltaics (not including solar thermal systems such as CSPs) and wind power, are presented with the three most utilized sources of non-renewable energy, nuclear power, coal and natural gas. Additionally, the sum of the electricity generated from the three renewable sources is illustrated.

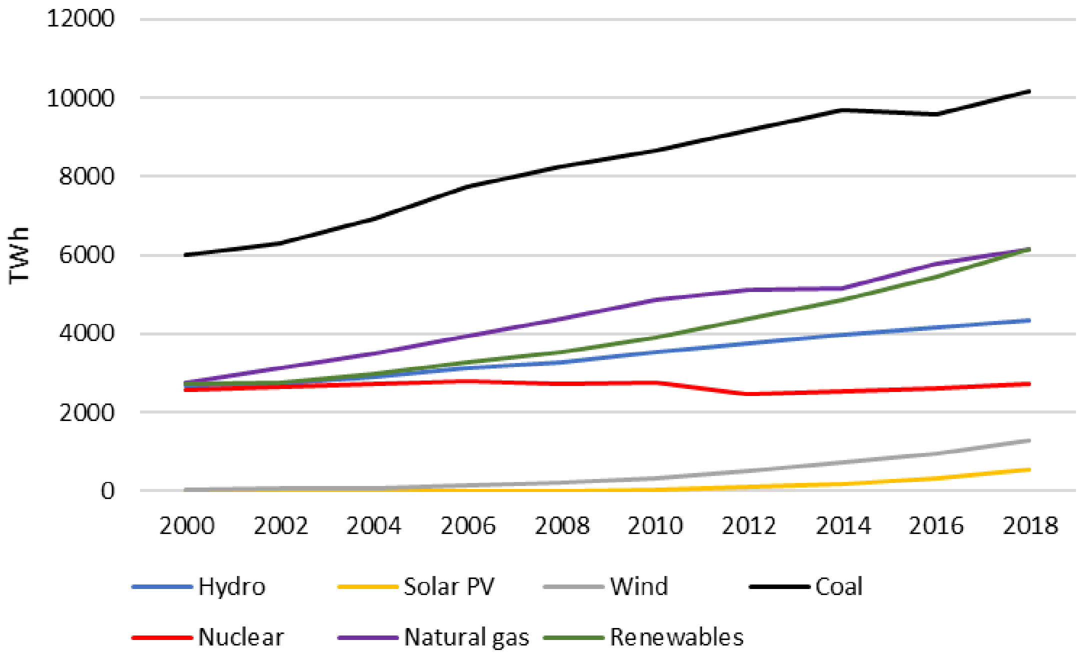

Figure 1. World electicity generation by source (IEA 2020b.)

As seen in Figure 1, all the renewable sources have increased their capacity, with hydro power leading as a more established source. Combined, the renewables have surpassed natural gas in the recent years while nuclear power's capacity has remained steady. Still, coal remains the most utilized source and its capacity has grown by almost 70%. As the electricity consumption of the world has kept increasing, from ~14 160 TWh in 2000 to ~24 740 TWh in 2018 (IEA 2020b), the renewable sources still require greater investments if the ambitious climate goals of different treaties and international organizations are to be fulfilled.

Jacobson & Delucchi (2011a) found that especially wind and solar PV are underutilized compared to their global potential, the current capacity being a fraction of the global maximum. Hydro power, instead, is an order of magnitude more utilized, while still having room for increase in its capacity. Most importantly, the authors found that there seems to be no constraints due to material shortages for heavily increasing the capacities of wind and solar PV in the future.

Still, however much there is underutilized capacity in renewable energy sources, costs play an important role in power generation decisions as with any consumer/investment decisions. Figure 2 summarizes the changes in levelized cost of electricity (LCOE) for new utility-scale PV investments in select countries (a) and the global average compared to on shore wind (b).

a)

b)

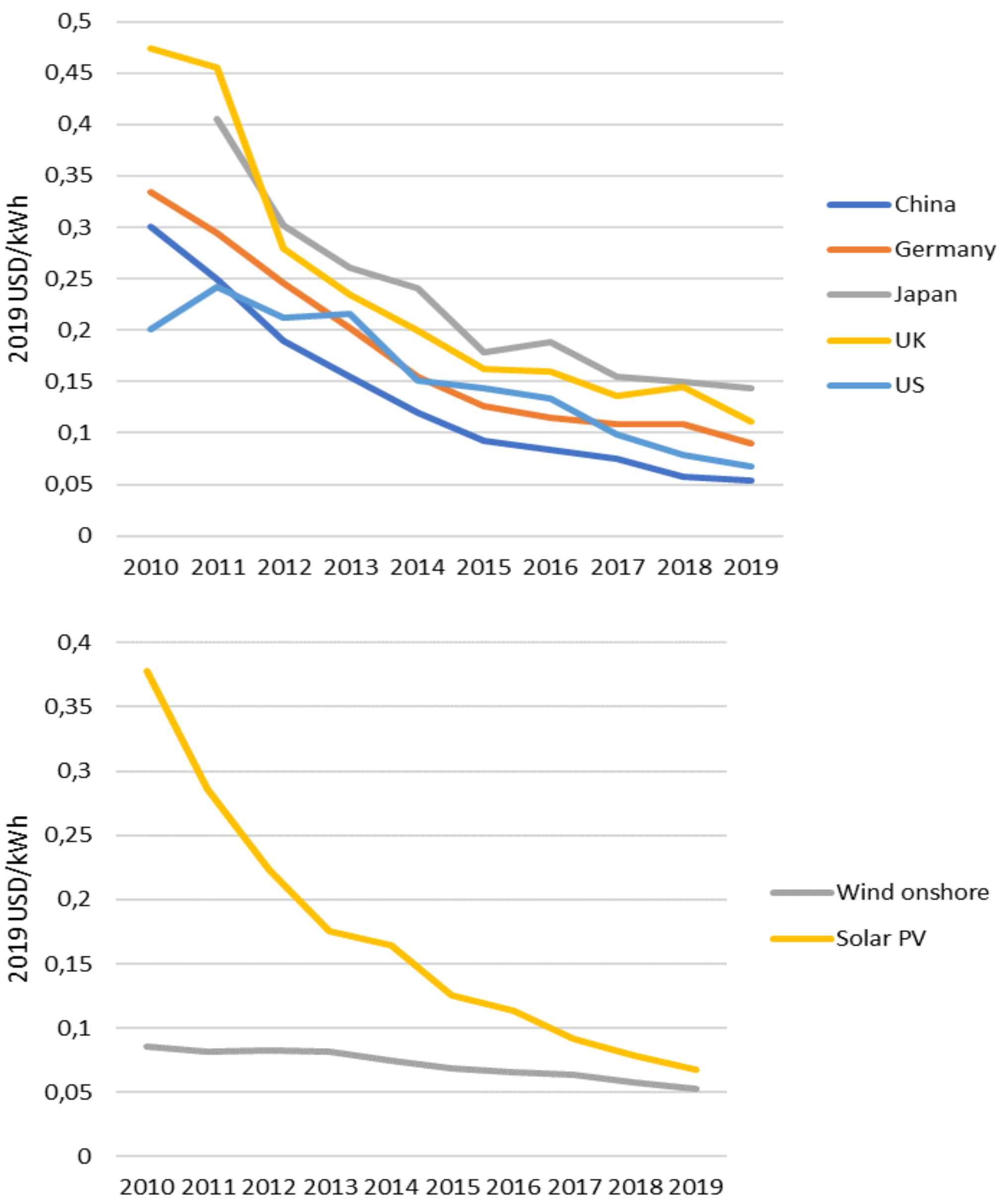

Figure 2. LCOE of solar PV and wind (IRENA 2020.)

As seen in figure 2, solar PV costs have decreased and become somewhat comparable to the costs of onshore wind installations. The decrease in costs is mainly driven by cheaper solar module prices and lower balance-of-system costs (IRENA 2020.) While the costs in figure 2 are calculated from larger, utility-scale solar investments, the same advancements can reasonably be expected to reduce costs in smaller, individual-scale solar system investments.

However, some caution should be used when dealing with LCOE, given by equation

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

where I_t is investment cost, M_t the maintenance and operation cost, F_t the fuel cost and E_t the energy generation at time t. The interest rate is denoted as r (the calculations of IRENA use interest rate of 7.5% for OECD countries and China, and 10% for other countries.) As can be inferred from equation 1, the costs given may vary substantially depending on the discount rate (cost of capital r) used for a particular energy investment. Moreover, LCOE heavily favors energy sources that require less time between initial investment and power generation. Finally, LCOE does not account for the different functions individual energy generators may play within a grid. For example, a power plant might only be dispatched when demand spikes occur, thus inflating the LCOE of the plant.

Still, looking at equation 1, some benefits of solar power can be identified. Solar panels need almost to maintenance (Motiva 2020), and they don't require fuel for power generation. As the technology has matured, the initial investment costs have gone down, while the increased efficiency of newer panels have translated to more electricity generated. Finally, if carbon emissions are priced into the equation, solar power has next to none. The only emissions are associated with the manufacturing of the solar modules and panels, and they are negligible compared to those of, for example, coal, oil or natural gas (Engül & Theis 2011.) Solar power can thus be an attractive source of electricity especially in region with higher annual solar irradiation.

On top of costs arising from individual solar systems, a large-scale adoption of solar power will entail also some integration costs from connecting individual systems to the local power grid. According to Hirth et al. (2015), these integration costs can further be decomposed to balancing costs, grid-related costs and profile costs, arising from uncertainty of production and forecasting errors, the disparity between the location of production and demand, and the temporal variability of renewable energy generation, respectively. In the case of solar panels on the roofs of Helsinki, especially balancing and profile costs might be noteworthy, but their quantities might be hard to assess. Assuming the electricity generated from individual panels would primarily be used by the residents of the same buildings, the grid-related costs might be negligible.

Regardless, all consumers might not be equally sensitive to price. Gadenne et al. (2011) found that individuals holding pro-environmental beliefs may be willing to pay a premium on green choices, but costs still constitute a barrier for environmentally conscious behavioral intentions. The adoption of solar panels in Helsinki cannot thus be assumed to be uniform based on costs only. Furthermore, in the study of Gadenne et al. (ibid.), social and community influence was determined to be positively correlated with environmental behavior attitudes, which in turn translate to environmental behavior. Thus, on top of the reduction in prices, the adoption of solar panels might benefit from a critical mass of consumers investing in them and contributing to the visibility of these kinds of systems in a community.

Graziano and Gillingham's (2015) study on the diffusion of solar PV systems in Connecticut seem to support the hypothesis that the so-called 'peer effects' (the prevalence of a given technology among individuals being contingent on neighbors, close-by peers) play an important role in the adoption of solar panels in a community. While the cost of electricity and a local incentivizing program were significant predictors of solar panel diffusion in Connecticut, the adoption of such systems followed localized clusters, i.e. households seemed to be more likely to invest in solar panels if they saw their neighbors doing the same.

Still, the adoption of solar power is not without its challenges. As hinted by the discussion of integration costs earlier, one notable downside of solar panels is the inherent variability of solar radiation both by the time of day and the seasons of a year. This means that power grid operators need additional measures to balance the grid i.e. match the generation and demand, if the solar power is to be fed into the grid. Regarding short term variability in electricity generation, Jacobson and

Delucchi (2011b) identify seven distinct ways to address the problem in their model for a power system consisting entirely of renewable energy sources:

1. using interconnected and spatially dispersed uncorrelated energy sources
2. using constant energy sources to fill the gaps of variable electricity generation
3. using different demand-response management methods to schedule electricity usage that is not time-sensitive to match variability
4. storing surplus electricity for later use
5. storing surplus electricity in electric-vehicle batteries
6. increasing the capacity of variable sources, so that the times demand surpasses generation are fewer
7. combining weather forecasting with power generation to minimize forecastable variation.

What would this then mean for a possible large-scale adoption of solar panels in Helsinki? The system would need to be connected with for example a source like wind (1), since the covariance of the combined sources could be smaller than the variability of either one individually, and additionally hydro (2), so that the gaps in solar power generation might be covered by dispatchable hydro power. The system should also incorporate weather forecasting (7) and demand schedulers (3) with individual solar systems. Storage in batteries (4) by the solar panels and in the batteries of electric vehicles (5) could further balance the load of the grid on top of forecasting and schedulers. Finally, increasing the coverage of solar panels (6) would obviously increase the ratio of generation capacity to peak demand, thus decreasing the time the panels could not produce enough electricity.

It is important to note that the variability of solar power generation can be further divided to the more deterministic variance arising from the position of the sun, based on the time of day and the season of year, and the more stochastic variance (Anvari et al. 2016), within individual hours arising from passing clouds. While the deterministic variance can generally be somewhat easily forecasted by e.g. using past data to infer patterns based on time of day and year, the stochastic variance can't be. Looking at the strategies proposed by Jacobson and Delucchi

(2011b), one might hypothesize that strategies number 1, 4 and 5 could help address the stochastic variance, while numbers 4 and 5 could of course help with the deterministic variance as well.

Indeed, Mills and Wiser (2010) found that the short-term stochastic variance can be effectively combatted by spatial dispersion. Studying data from the states of Kansas and Oklahoma in the U.S., Mills and Wiser concluded that geographic diversity of 20 kilometers between solar panel sites could bring the aggregate variance down, thus decreasing the efforts and costs of balancing the power grid, in the case that the individual solar panels are treated as a collective part of the grid.

Of course, the deterministic variance of solar irradiance can also become a problem if forecasting is not accurate. Forecasts based on past data, e.g. time-series analysis or weather forecasts based on physical measurements can be accurate when local weather is relatively stable. However, when unexpected and abrupt weather changes occur, the aforementioned forecasting methods fall flat. To prepare for these situations, the conventional methods can be combined with machine learning based models with shorter term forecasting windows that have been successful, for example models based on neural networks. (Hossain et al. 2017). In any case, both the deterministic and stochastic variability of solar power would entail integration costs in any grid with notable solar system penetration.

The inclusion of surplus electric storage could be beneficial when assessing the potential of solar power in Helsinki. Lim et al. (2020) found that in a residential setting, combining (stationary) batteries and solar systems both decreases the average electricity costs and reduces variance in a grid's balance. Including demand scheduling for individual homes further decreased both statistics. Moreover, it was found that there were external benefits to even those homes that did not partake in the adoption of said systems, as smoother overall grid balance reduced the peak costs of electricity. On top of stationary batteries, energy storage in electric vehicles could also be beneficial for Helsinki, were enough coverage present. However, as of 2019, electric vehicles (including hybrids) constituted less than 1 % of registered passenger cars in Finland (Tilastokeskus 2020b.)

As can be inferred from the challenges of solar systems and solar power alone, the challenges become grid-level if and when solar panels (and other types of variable electricity supply) have a considerable share in the production capacity. Consequently, the power grids need to have enough flexibility in terms of supply-demand balancing to combat the variability of renewable energy sources. Lund et al. (2015) focused their study on the flexibility measures required in a power grid in the case of wide penetration of renewable energy sources. On top of the strategies identified by Jacobson and Delucchi (2011b), the authors also stress the importance of the grid infrastructure itself, with smart grids (all stakeholders connected via intelligent ICT), micro grids (smaller local grids servicing a small area) and super grids (high voltage lines for transmission from remote plants) as examples. In the case of Helsinki, the individual solar systems might be connected to a smart grid, where the sum of individual outputs and demands could be collectively balanced and redistributed to match spatial imbalances.

Still, flexibility might be a feature power grids possess inherently. Simulating Europe's electricity markets up to 2050, Bertsch et al. (2016) found that, following an exogenous increase in the share of renewable sources in the production mix, as imposed by current climate policies, investments would favor those conventional energy sources that are cost-efficient even with reduced uptime. These plants would lend the electricity system flexibility to combat the short-term variance in renewables. Additionally, some quickly dispatchable sources, such as gas-powered plants with carbon capture and storage capabilities would be invested in for the role of backup reserves in times of low renewable yield. Thus, the simulation provided evidence that the flexibility of the new mix of energy sources was a by-product of the competitive markets, meaning that policy makers would not necessarily need to offer additional incentives for investments in flexible sources.

2.2 Solar power in Finland

As a northern country, Finland's geographic location presents some unique challenges to the utilization of solar power on top of the challenges discussed earlier. The seasonality of solar radiation becomes more extreme the further from the equator a country is located, and thus Finland receives notably less irradiation in winter compared to summer. The decrease is naturally higher in Northern Finland than in the southern parts of the country. Figure 3 illustrates the variance in total horizontal solar irradiation by month in Vantaa, in Southern Finland, and Sodankylä, in Northern Finland. It is also important to note that in order to maximize electricity production of solar panels, they should be optimally oriented both in terms of cardinal directions and panel inclination based on the geographic location. For example, the total annual yield in Vantaa with horizontal panels is ~975 kWh while south-facing panels with a 45° inclination (the optimal) yield ~1205 kWh (Ilmatieteenlaitos 2020.)

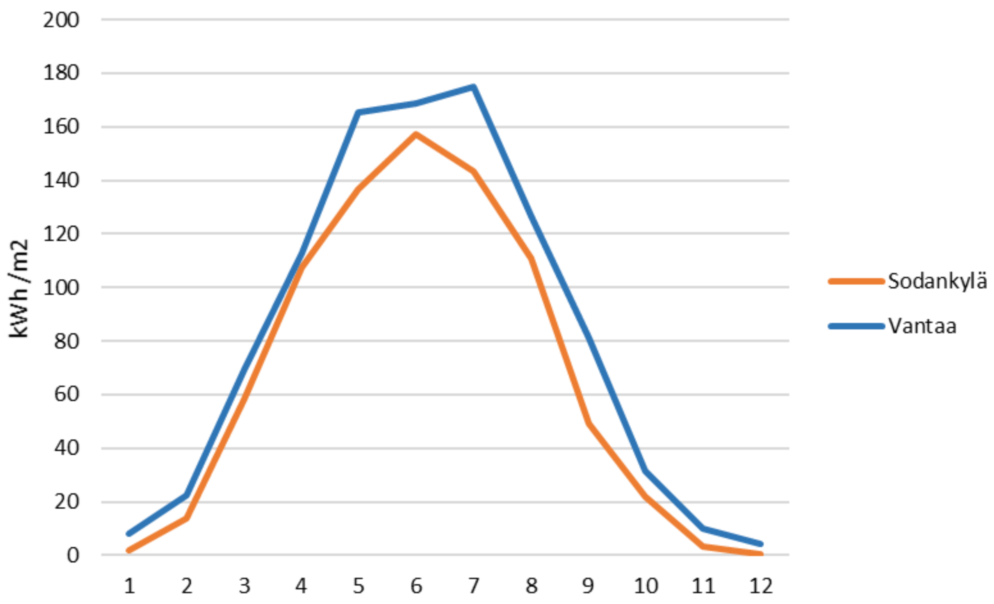

Figure 3. Total Solar Irradiance in Finland by month (Ilmatieteenlaitos 2020.)

As discussed before, heating is the number one source of pollution in Helsinki (Helsingin kaupunki 2018), and it is naturally concentrated on the winter months. With the minimal solar irradiation during winters, utilizing solar panels in Helsinki might not be the best way to decrease pollution and carbon emissions arising from heating buildings. Moreover, more than 90% of the buildings in Helsinki get their heating from a district heating network (Helen 2019), where the heat is produced in centralized power plants and then transported to buildings via heated water in underground pipes (Motiva 2017.) Thus, without a sizeable increase in electric heating with e.g. electric heat pumps, reducing the emissions associated with heating could be achieved by moving to more sustainable sources in the power plants. The electricity generated with solar panels could then be used to for other demand, such as powering general electrical appliances.

Regardless, solar power has remained marginal in the electricity production in Finland (147 GWh in 2019 or 0.2% of total production), while the most prominent source in domestic electricity generation is nuclear with ~22.9 TWh of production in 2019. Other notable domestic sources in 2019 were hydro power with 12.2 TWh and biofuels (mainly wood-based fuels) with 12.5 TWh of production. Fossil fuels, including e.g. coal, natural gas and peat, constituted combined 11.9 TWh of electricity production. Finland also imported ~20 TWh of electricity to satisfy the overall demand for electricity. (Tilastokeskus 2020a).

In a study on the Finnish electricity markets, Salmela and Varho (2006) found several obstacles in consumers' decision to purchase green electricity. Firstly, the interviewees lacked knowledge on the green electricity alternatives and were distrustful of the intentions and motives of the electricity suppliers. Secondly, the time and effort required to both research and then switch to the green alternatives were seen as notable barriers. Finally, economic reasons such as the higher cost of green electricity were important to the interviewees even though many of them had not actually looked up these prices. However, in accordance to the study of Gadenne et al. (2011) discussed in Section 2.1, some of the interviewees of Salmela and Varho expressed a willingness to pay a premium on green alternatives.

It can be assumed that, following the attention climate change (and the role of carbon emissions in it) has gotten in recent years, Finnish consumers might nowadays be more aware of green electricity choices and in conjunction solar power. Additionally, as the prices of solar modules and the associated equipment have gone down, the cost barriers of solar adoption can be expected to diminish. Still, the time and effort required to both research potential solar system providers and actually implement them can be considerable. An important notion to consider is that, due to the mix of public and private buildings, and consequently, roofs in Helsinki, a large-scale adoption of solar power is not possible without incentivizing private citizens. The incentivizing methods are subject to policy makers' preferences, but different schemes can of course have varying levels of success.

Scarpa and Willis (2010) classify incentivizing schemes to awareness measures, command and control methods, (e.g. through building codes), and market-based instruments (e.g. investment subsidies or tax exemptions). Studying the preferences and willingness of consumers to pay for renewable alternatives in the U.K., Scarpa and Willis found that the initial capital costs were more important than ongoing electricity savings through household renewable electricity generation from for example solar panels. Of course, as discussed earlier in this thesis, the costs of solar systems have gone down in the recent years. Still, the success of a possible optimal allocation of solar panels on the roofs of Helsinki is contingent on the willingness of households to invest in such systems.

As of the time of writing this thesis, three kinds of market-based instruments exist in Finland that aim to accelerate the push towards greener energy infrastructure, presented in table 1 below.

Table 1: Market-based incentives for renewable energy (Motiva 2020.)

Instrument	**Private persons**	**Apartment house companies, ARA organizations(1)**	**Companies, municipalities, other organizations**
General tax credit for household expenses	x		
ARA(2) investment subsidy	x	x	
Governmental investments subsidy(3)			x

(1) Non-profit organizations focusing on public social housing
(2) The Housing Finance and Development Centre of Finland, governmental agency
(3) “Energy aid”, granted by The Finnish Ministry of Economic Affairs and Employment

The general tax credit is based on the working costs in house improvement projects (including e.g. solar power systems). The credit is intended for private persons, and the percentage and maximum amount of work that can be deduced with the credit varies based on the year of the improvements. (Verohallinto 2020). The ARA investment subsidy can be granted for 10% of solar power investment costs, with a maximum of 4 000€ or 6 000€ based on the energy efficiency of the installation. However, an individual investment can only be subsidized either with the tax credit or an ARA subsidy. (ARA 2020). Finally, the governmental investment subsidy is calculated on a case-by-case basis. In contrast to the other instruments, the governmental subsidy is only granted to investments that would not be undertaken without the grant. Consequently, the subsidy must be applied for before the investment has been started. (Työ- ja elinkeinoministeriö 2020).

In the case of solar panels in Helsinki, the possible subsidies available for individual installations would be contingent on the ownership of individual roofs (buildings). Thus, accurate cost reductions on the collective level are hard to assess without building-level information on the ownership status. On the other hand, all owners of individual solar systems have the option of selling surplus energy back to the grid. An appropriate contract with an electricity supplier is often required, though. For example, Helen (2020) buys surplus electricity on spot market prices from homes with an electricity contract with the company and a solar installation with a maximum power of 100kW. Additionally, if the city of Helsinki wants to further incentivize private citizens to adopt solar systems, some awareness measures might be in order. These could help combat the perceived effort/burden of researching and implementing greener energy choices, as mentioned in the study of Salmela and Varho (2006) discussed earlier.

Of course, incentivizing potential solar panel adopters is not only the goal of the city of Helsinki, but solar panel providers as well. Strupeit and Palm (2016) studied how these companies have combated the typical barriers of solar system adoption. The barriers include consumer inertia (1), high initial investment costs with long investment horizon (2), difficulties in planning and installation of the systems (3) and insufficient information and concerns about the technology (4). The strategies to overcome these barriers include for example:

1. advertising, using existing sales channels, using non-commercial partners, peer-effects
2. pay-per-use, support on loan programs, advice on governmental incentive schemes
3. customized turnkey products, advice on planning and installations
4. efficiency and product warranties, maintenance contracts, certifications on producers and installers.

How do Finnish companies utilize the aforementioned strategies? Let's take Helen as an example, an electricity company owned by the city of Helsinki. Naturally, Helen is able to leverage its existing electricity customers when selling solar installations, thus using existing sales channels. The company offers turnkey solar systems including planning and installations and offers financing for said systems. Helen also gives potential customers in-depth advice on the systems and governmental incentivizing programs, namely the general tax credit. Finally, Helen offers efficiency and product warranties for their solar installations. (Helen 2020).

While the previous example was based on one company, the solar system providers in Finland have very similar offerings in general. Notably most of the largest electricity companies also provide solar installations. Still, there might be room for more partnering with public institutions if policy makers want to promote solar power adoption. Especially in the case of Helsinki and its goals regarding carbon reduction, when the city already owns an electricity provider, a common advertising and marketing effort would undoubtedly increase the awareness and knowledge potential customers have on solar power and the associated installations.

3 Spatial decision making and Geographical Information Systems (GIS)

According to Stone (1998, pp. 66) ‘Geographic Information Systems are hardware, software, and digital geospatial data combined to provide mapping capabilities, databases of geographic and feature information, and spatial analysis’. In other words, geographic information systems (GIS) are used to capture real-world objects, e.g. the coordinates of roads and buildings, and their features, e.g. area and size, in a computer-readable format. These digital geographic models can then be used in conjunction with analysis software to provide spatial analysis to support decision making. Thus, the field of GI systems is closely linked to the academic field of spatial decision making, the GI systems often being used to support spatial decision making.

However, the abbreviation GIS can also refer to geographic information science. Whereas GI systems are concerned with the mapping of objects and their features, GI science concentrates on the conceptual frameworks on how these kinds of systems should be designed and implemented. Thus, the advances in GI science translate to better GI systems. (GISGeography 2020). Regardless, in this thesis GIS is used to refer to geographic information systems.

The advances in computing power and the substantial decrease in the associated costs have made GIS applications more available to the public, and thus they are used as decision support systems in all kinds of planning processes. These processes include, for example, urban planning, transportation and logistics, and military planning. The ability of GIS applications to efficiently record geographic relations has made them a staple support system in spatial decision making. (Maliene et al. 2011).

The rest of Section 3 is focused on the findings of a literature review conducted on spatial decision making. Topics include the developments, real-life applications and challenges in spatial decision making and spatial modelling. While GI science and the underlying principles in designing GI systems are of course important, the focus of this thesis is on the practical application of spatial data. Thus, the modelling of real-life decision problems is more relevant to the goal of creating a model for optimizing the allocation of solar panels and assessing the viability of solar power on the roofs of Helsinki.

3.1 Spatial Decision Making

According to Malczewski (2006), spatial decision problems often have a large group of feasible alternatives and multiple assessing criteria that may be at odds with each other. At the same time, there may be many decision makers with different preferences. Following a literature review, Malczewski categorizes these kinds of GIS-based multicriteria decision problems based on six classifications, where the first three are mainly attributable to the characteristics of individual GIS applications and the latter to spatial decision making:

1. raster vs. vector-based data
2. implicitly vs. explicitly spatial criteria
3. implicitly vs. explicitly spatial alternatives
4. multi-attribute vs. multi-objective decision problems
5. individual vs. group decision makers
6. deterministic vs. uncertain decision environments.

To give substance to these classifications, consider the problem of allocating solar panels on the roofs of Helsinki. The data is in the form of a shapefile, thus the coordinates and shape of individual roofs are depicted in vectors (1), while the attributes are in a separate file accompanying the shapefile. The criterion of electricity generation is implicitly spatial, as the yield is based on the location of individual roofs, whereas the criterion of area is explicitly spatial (2). The decision alternatives of the problem are subsets of roofs, and thus the alternatives are explicitly spatial (3). The problem has multiple objectives (4), namely cost/area minimization and yield maximization. Following the mixture of public and private properties of Helsinki, the problem ultimately has a large group of decision makers (5), consisting of the city, businesses and private citizens i.e. the owners of individual buildings/roofs. However, as it is impossible to infer individual preference/utility functions for all the decision makers, costs and yield are assumed to be the driving factors behind the value of solar systems. Thus, the problem of allocation is treated as having an individual decision maker, harmonizing the objective function to being equal for all. Finally, the decision environment is treated as deterministic (6), i.e. the electricity generation is assumed to be stable from year to year. Of course, in practice, the annual yield of any one roof is uncertain. Additionally, the allocation cannot be enforced, thus making the adoption of solar panels also uncertain. Still, for practicality's sake, the yield is assumed to be constant in this study. Because the goal is to assess the viability of large-scale solar panel utilization, different allocations are examples and do not necessarily reflect real-life adoption.

In contrast to the vector-based data on the roofs of Helsinki, sometimes it's more appropriate to use raster-based spatial data, i.e. treating the areas in focus on a grid-basis. A recent example from Finland is the pro gradu study of Sydänlammi (2019), where grid-based data on the population of Helsinki was used to optimize the school districts of the city. The motivation behind the optimization was to combat segregation between Helsinki's areas, arising from the varying social compositions of students in different school districts.

In the context of solar power, grid-based data might be used to find suitable locations for utility-scale solar plants, for example. Were Helsinki interested in investing in a CSP (see Section 2) plant, a grid of Helsinki with solar irradiation yield and availability of land as attributes of individual grid blocks might be used to gauge different possible sites for the plant. Continuing the example of a CSP plant, a siting problem of an individual solar plant would presumably have a finite and relatively small number of possible location alternatives due to the requirements of such plants. According to Malczewski (2006), these kinds of selection problems with limited decision alternatives but multiple attributes (of alternatives) are typical multi-attribute decision problems.

Regarding multi-objective decision problems, a good example is the study performed by Christensen et al. (2009) on the optimization of protected (conservation) sea area placement, with competing criteria such as economic (fishers' revenues), ecological (biodiversity) and social (jobs from fishing) objectives. The different objectives are compiled into a single objective function, where individual (weighted) objectives are summed together. The area under optimization is partitioned into cells, and the protected area was gradually increased by choosing cells that maximize the objective function until a given protection level is reached. Similar to the problem of solar panel allocation in this study, different levels of protection (adoption rates for solar panels) might be calculated to assess different scenarios. However, the problems differ in the nature of the area under consideration, in the case of the roofs in Helsinki the area being naturally non-continuous compared to the continuous sea are.

Malczewski (2006) notes that multi-objective spatial problems are often solved by converting the objectives into a single objective problem, and then solving the acquired problem using basic linear programming methods. As there are only two principal components under consideration in this study, the area and yield of individual roofs, converting the competing objectives into a single objective should be feasible. The model would then be either maximizing electricity yield while having a constraint on the maximum area the allocation could take, or alternatively minimizing the area used for a given electricity production level.

Due to the nature of solar power and its dependency on location, spatial optimization has often been utilized in the literature concerning solar installations. Azadeh et al. (2006) ranked potential solar plant locations using Data Envelopment Analysis (DEA), where, put simply, individual alternatives are compared by their efficiency of converting a set of inputs into outputs (where higher efficiency is of course better). The study had a hierarchical approach by first comparing 25 individual cities in Iran, and further analyzing 6 different districts/regions within each city. Similar methods could be used in Helsinki as well, if the goal was to find, for example, the most suitable districts of Helsinki for solar power. One might use the availability of rooftop area and electricity yield as attributes of each district, and then rank them according to their efficiency between inputs (roof area) and outputs (electricity generation).

Also concerning solar plants, Sanchez-Lozano et al. (2016) studied the best suitable locations for solar power in Spain. However, a much larger set of 66,845 locations were assessed using both TOPSIS, a method where alternatives are ranked based on their distance from both positive (closer better) and negative (further better) ideal solution, and ELECTRE TRI, where alternative’s pair-wise comparisons regarding decision criteria are used to classify and rank alternatives into predefined categories.

All the methods discussed above, DEA, TOPSIS and ELECTRE TRI, are used in ranking of alternatives when multiple attributes are present. Similar methods have been used to support decision making in other sustainable energy planning studies as well (Pohekar & Ramachandran 2004.) In the context of the roofs of Helsinki, the three methods might be used to find the best alternatives were more than the area and yield of individual roofs considered. For example, there might be preference for roofs in some districts of Helsinki or buildings with worse energy efficiency might be prioritized. Still, without absolute control on the placement of solar panels on individual roofs, this kind of analysis would only serve as informative and raising awareness about the potential of solar power, were the analysis conducted on all of the roofs in Helsinki. On the other hand, the city of Helsinki could use these kinds of methods for assessing the roofs on the buildings it owns. Adding solar panels on publicly owned roofs might then be used to provide electricity for individual buildings, potentially offsetting electricity produced using carbon-intensive sources, such as coal or natural gas.

On a larger scale, spatial decision analysis has also been used in in the context of planning renewable energy infrastructure. Lenzen et al. (2016) used simulation to assess the power infrastructure in Australia. The simulation was based both on hourly demand-supply matching during a year and a grid-based location optimization of proposed renewable energy plants. Additionally, the transmission network between generation and demand locations was optimized. The total costs of the resulting energy source mixes and locations were calculated with varying attribute levels, e.g. the price of carbon emissions and backup power capacity, to assess different possible scenarios. Similarly, a large-scale utilization of the roofs of Helsinki for solar power would merit a more comprehensive study on the effects of high renewable energy penetration on the power grid in Helsinki. While this kind of analysis is out of the scope of this study, future research could prove useful if/when variable renewable energy sources become more wide-spread.

While there is a lot of literature concerning the placement of individual solar farms i.e. larger utility-scale plants, there seems to be relatively little literature on the spatial optimization of a large-scale rooftop solar panel adoption. While many researchers study rooftop solar systems and acknowledge their merits (see e.g. Graziano & Gillingham 2015, Jacobson & Delucchi 2011a discussed in Section 2), the approaches in these studies have been more descriptive and normative rather than prescriptive in the sense of practical adoption suggestions. One possible explanation could be that there might not be roof-level data in many areas and countries, while solar irradiation maps on a grid-basis are found for most of the world.

A recent example concerning rooftop solar systems was the study of Zhong and Tong (2020), where the objective was to cover a suitable roof with solar panels as efficiently as possible. The authors used LiDAR (3D imaging with laser light) to first identify the suitable areas of a single rooftop and then optimized the allocation of panels to minimize the suitable area not covered by panels. While the scope of the study was of course different from assessing all the roofs of Helsinki, similar imaging techniques might be used in Finland as well, for example to supplement the dataset used in this study when new buildings are built in Helsinki.

4 Methodology and modelling

The problem of panel allocation has ultimately a large group of decision makers, as discussed in Section 3.1. The sheer size of the group makes it impractical to assess different preferences the decision makers might have, or whether they hold environmental attitudes that would make them more inclined to adopt solar power. Consequently, the individual utility functions can't be inferred. Thus, for practicality's sake, it is assumed that the cost of solar systems is the defining factor for individuals' utility from solar panels and driving their adoption, i.e. individuals would invest in solar systems if they can save money utilizing them.

The cost function for an individual roof is modelled in the form of regular linear equation

$$cost_i = b + ca_i, i = 1,2,\ldots,m, \tag{2}$$

where $cost_i$ is the cost and a_i the area associated with the i:th roof, while b and c are constants. The exact cost function was derived using linear regression from data on the offerings of Lumo (2020), a Finish electricity company, yielding values $b = 2666.38$ and $c = 165.89$. The costs are based on a turnkey service, meaning that they include all the necessary equipment and installations for the customers, but no extra services, such as production tracking systems. The area of an installation seems to be a very good estimator on the price, as the regression has an R^2 statistic of ~99.52%, and both the area and intercept are statistically significant at a p-value of 0.001. The full statistics from the linear regression are reported in Appendix B. The company was chosen due to the relatively wide range of offerings and the availability of data. Note that the prices include Value Added Tax, which companies can typically deduct in their taxation. The cost function relates to a solar panel with a reported power of 280 watts and an efficiency rating of 0.172, manufactured by Green Energy Finland (GEF 2019.) Moreover, the panels have a linear efficiency guarantee for 25 years, meaning that at after 10 years the panels should produce at least ~90% of the expected yield, and at year 25 still ~80%.

As for the optimization model itself, the goal is to efficiently allocate solar panels on available roofs. Decision variables $x_i \ in \ [0,1], i = 1,2,\ldots,m$ are introduced denoting the share of i:th roof that is used for solar panels. The allocation has two competing objectives: on the other hand, we would like to produce as much electricity from our resources (roofs) as possible, while also minimizing the costs of the electricity produced. Still, as the allocation cannot be forced on individual roofs, it is more relevant to assess the optimal allocations given varying (hypothetical) production levels. The problem then becomes a linear programming problem with an objective of minimizing cost. As the cost of an individual solar system is highly reliant on its area, the objective function then becomes

$$min \sum_{i=1}^{m} x_i a_i, \tag{3}$$

where a_i is the size of the suitable area of roof i. The objective function is constrained by

$$\sum_{i=1}^{m} x_i \, e_i \geq \ T, \tag{4}$$

where e_i is the electricity production of roof i, and T is the target level of production, expressed as an absolute value. Setting the modeling problem in the aforementioned way should ensure that for each target level T, the model finds the subset of roofs that minimizes the needed area. Thus, pareto optimal solutions in terms of electricity yield and costs are expected to be found. The modelling was done using Python and an API for Gurobi optimizer. Gurobi optimizer is a commercial software package which can be used for a wide range of different optimization problems. A free limited-time academic license was used during the modelling. The source code for the model is presented in Appendix A.

5 Applying the model to the roofs of Helsinki

The open dataset used with the allocation model created in this study is provided by Helsingin seudun ympäristöpalvelut (HSY), and it was first published in 2015. The data contains information on the roofs of Helsinki, mainly the area suitable for solar panel installations, and the expected annual electricity yield of individual rooftops. The data has two layers, a raster of suitable roof area, and a vector-based layer depicting all the roofs in Helsinki with their suitable area size and electricity yield as attributes.

When determining the suitable sections of individual roofs for the raster layer, three criteria were used by HSY. Firstly, the section should get at least 847 kWh/m² of solar irradiation per year. Secondly, the suitable section of an individual roof should have an area of 5 m² at minimum. Lastly, the section should leave a free area of at least 0.5 meters wide from the edge of the roof. When calculating the electricity yield, it was assumed that the panels fully cover the suitable area and that they are installed parallel to the roofs, regardless of the roofs' inclination. The efficiency coefficient used for the panels was 0.15. The original vector data contains 87 837 roofs. Some roofs may have parts that satisfy the solar irradiation and free-area-from-edge criteria, but the roof might not have a total suitable area of 5 m². Nonetheless, the vector data includes these roofs and has the suitable area as an attribute for each roof. Upon initial inspection, 50 917 roofs were found to contain no suitable area for solar panels, leaving a set of 36 920 individual roofs under consideration. If using the 5 m² criterion, 35 586 roofs remain.

5.1 Results of the optimization

To illustrate different production scenarios, the roof allocation model was run with different target levels of solar power generation in mind. Additionally, the model was run both treating the roofs as binary variables and continuous in range [0,1]. The minimum viable area the roofs might need to have, 5 m² as determined by HSY, was also considered. Tables 2 and 3 summarize some key statistics obtained with the optimization, differing in the variable type used for the roofs and the presence of a minimum viable area constraint. Note that the electricity generation in the tables is calculated with the original efficiency rating of 0.15. The "area used" ration compares the combined area of an allocation to the total suitable area available on the roofs of Helsinki. The "roofs used" ratio compares the count of chosen roofs in a particular allocation to all the roofs in Helsinki, thus including even the roofs without any suitable area for solar panels.

Table 2: Production scenarios without minimun viable area, continous roofs

Target production (%)	Electricity produced (GWh)	Area used (%)	Roofs used (%)
0.1	79.4	0.095	0.069
0.2	158.8	0.192	0.105
0.3	238.2	0.291	0.122
0.4	317.6	0.389	0.142
0.5	397.0	0.489	0.163
0.6	476.4	0.589	0.185
0.7	555.8	0.689	0.216
0.8	635.2	0.791	0.250
0.9	714.6	0.894	0.303
1.0	794.0	1.000	0.420

Table 3: Production scenarios with minimum viable area = 5m², binary roofs

Target production (%)	Electricity produced (GWh)	Area used (%)	Roofs used (%)
0.1	79.4	0.095	0.067
0.2	158.7	0.192	0.100
0.3	238.1	0.291	0.118
0.4	317.5	0.389	0.137
0.5	396.8	0.489	0.157
0.6	476.2	0.589	0.179
0.7	555.6	0.689	0.208
0.8	634.9	0.791	0.242
0.9	714.3	0.894	0.293
1.0	793.7	1.000	0.405

Looking at the results of the optimization, there seems to be little variance between the different approaches for modelling the roofs. Most notably, the optimization seems to offer limited benefits at first glance, as the total areas of different optimal allocations seem to be only marginally smaller than the respective production levels. This would imply that while individual roofs differ in size and thus electricity yield, the ratio between the yield and area seems to be relatively constant across the roofs. Were there large discrepancies between e.g. the districts of Helsinki, we would likely see much smaller area ratios for the lower production levels, and then progressively higher ratios for the larger production levels. Yield/area ratios were calculated to gain additional insight on the usefulness of the roof allocation model. Figure 4 presents the ditribution of yield/area ratios for roofs that have at least some suitable area for solar panels, i.e. $a_i > 0$.

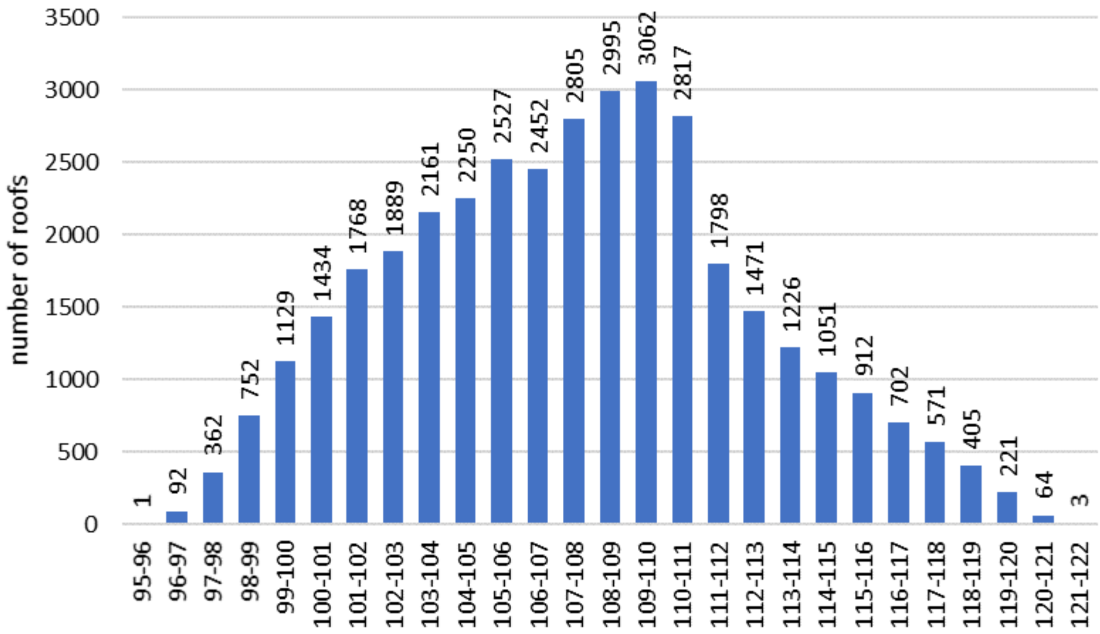

Figure 4. Variation of yield/area ratio between roofs

There is indeed some variation between the individual roofs, and the optimization model can be expected to choose the roofs that have higher ratios, i.e. the ones towards right in the figure. The minimum of the ratios was 95.920, the maximum 121.431, the mean of the ratios was 107.520 and the standard deviation 4.915.

To further assess the optimization model, a random order allocation was calculated as a base line, depicting non-optimal solar system adoption. The base line model randomly chooses subsets of roofs for solar panel adoption, i.e. roofs are chosen one by one until a production target level is reached. The roofs used for the base line model were those having a suitable area of at least 5m². The model was run 100 times for each target level, and a mean total area was calculated for each production level. The source code for the baseline model is presented in Appendix C. Looking at the “area used” ratios of the base line random choice model in table 4, the optimization seems to offer at least some benefits. The ratios are higher with the random adoption model across all the production levels compared to the optimal allocations.

Table 4: Area ratios of the random adoption model

Target production (%)	Area used (%)
0.1	0.1001
0.2	0.2002
0.3	0.3001
0.4	0.4001
0.5	0.5002
0.6	0.6001
0.7	0.7001
0.8	0.8001
0.9	0.9001
1	1

What about geographic dispersion then? Figures 5, 6 and 7 depict the optimal allocations of solar panels in Helsinki on various production levels. There seems to be no notable preference in the allocation of roofs between different areas in Helsinki. For each target level, the allocation seems to follow only the physical number of buildings in the different subareas/districts of Helsinki. Consequently, the subareas become more densely populated with solar panels as the target production level increases. This further demonstrates that the ratio between electricity production and the suitable area size is relatively constant across Helsinki. While there exists variance between the yield/area ratio between roofs, the variance seems to be somewhat uniform across Helsinki. For example, were an area much more suitable for solar power in Helsinki, we could expect the area to be fully utilized already on lower production target levels.

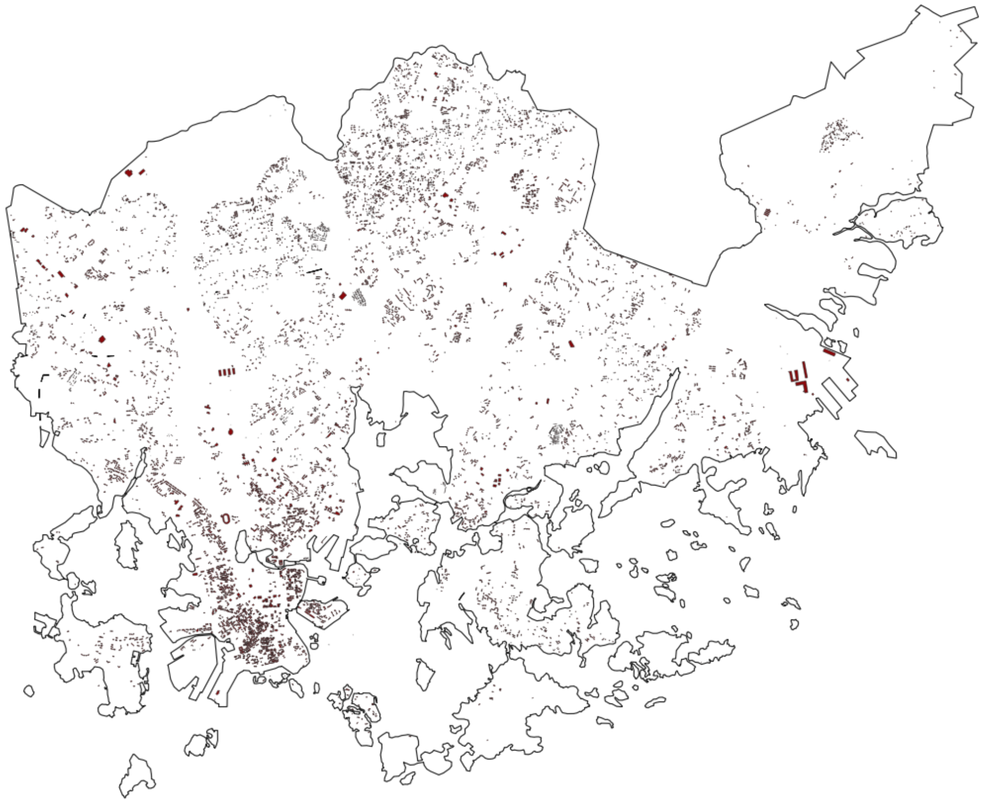

Figure 5. Solar panel allocation with 25% target level

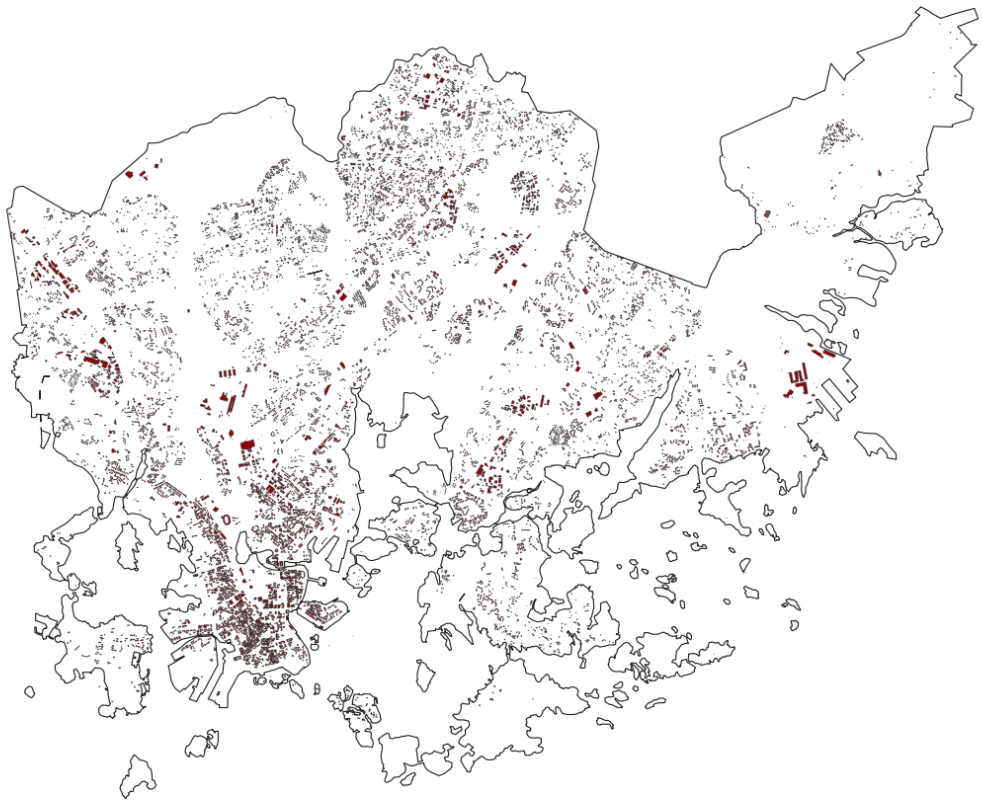

Figure 6. Solar panel allocation with 50% target level

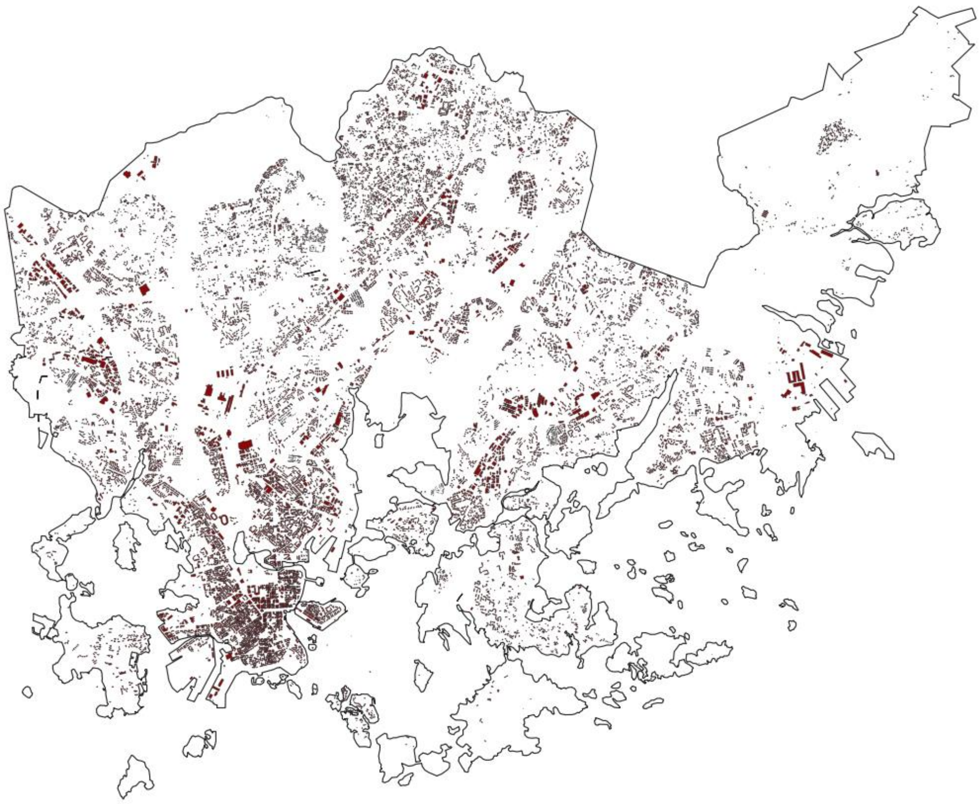

Figure 7. Solar panel allocation with 75% target level

QGIS was used to visualize the different allocations. QGIS is an opensource GI system, allowing conditional representation of vectors. Thus, the original data on the suitable areas of individual roofs can be combined with the output of the model (decision variables mapped to roof ids), and different production levels can be easily visualized.

Of course, any level of solar adoption is unlikely to happen if the cost of the electricity produced is not competitive with the consumer prices offered by local electricity providers. The combinations of roofs selected by the model were assessed using levelized cost of electricity (LCOE), given by equation 1. As discussed in Section 2.1, using LCOE has some caveats and drawbacks, but as it is widely used and relatively simple, calculating the levelized cost of various solar panel adoption levels makes comparison with other projects and local electricity prices in Helsinki possible. When calculating the energy production of individual years, a linear reduction in yields was assumed in accordance with the efficiency guarantees of the panel provider GEF, so that at $t = 1$ years the yield is 100% and at $t = 25$ years the yield is 80% of the initial year. Furthermore, the electricity yields were adjusted to reflect the slightly higher efficiency rating 0.172 of the GEF panels compared to the rating (0.15) used in the base data. The investment horizon was assumed to be 25 years with no salvage value at the end of the period. In accordance to the calculations of IRENA (2020), the interest rate used for OECD countries can be either 7.5% for utility scale systems or 5% for residential installations. The rate is smaller for residential systems because it is assumed that their owners tend to use the generated electricity themselves, thus requiring smaller rate of return on their investment. The initial investment cost is assumed to take place at $t = 0$ years.

The LCOE is also highly dependent on the operation and maintenance costs M_t used. For example, European Commission (2019b) has used an estimate of 3% for the operating and maintenance costs of photovoltaic systems, in terms of percentage of the initial capital expenditures. In this study the same level of 3% was used. The operating and maintenance costs include for example cleaning the panels, the expected one-time replacement of the installations' inverters (Motiva 2020) and any damaged cabling. Finally, the LCOE was calculated from the allocations obtained when treating the roofs as binary variables and considering only the roofs with suitable area of at least 5m^2. The exclusion of smaller roofs can be expected to give a more realistic estimate for the LCOE as small installations might be hard to implement in practice. Table 5 presents the LCOEs calculated on various target levels, and with the different interest rates. The costs are relatively similar between different target levels within both interest rates, but naturally with the higher discounting rate the costs are higher when the initial investment is given more weight.

Table 5: LCOE of the allocations

Target	LCOE (cent(€)/kWh)	
	r = 0.05	r = 0.075
0.1	15.70	18.43
0.2	15.45	18.15
0.3	15.26	17.91
0.4	15.19	17.83
0.5	15.17	17.81
0.6	15.18	17.82
0.7	15.23	17.88
0.8	15.30	17.96
0.9	15.43	18.12
Mean	**15.32**	**17.99**

The mean values were then compared to the historical data of consumer electricity prices in Finland. Figure 8 depicts monthly total consumer prices starting from January 1997 and ending in November 2019, with the calculated mean LCOEs. The total prices include the cost of electricity, the transfer fee and the energy tax. The prices of individual months were calculated as the average of different typical consumer groups, such as apartments (both residents and e.g. small businesses), small residential buildings and agriculture. The prices exclude manufacturing and similar industries. Note that the cost of electricity is based on a price that is guaranteed to consumers, so electricity companies may have offerings with lower prices from time to time.

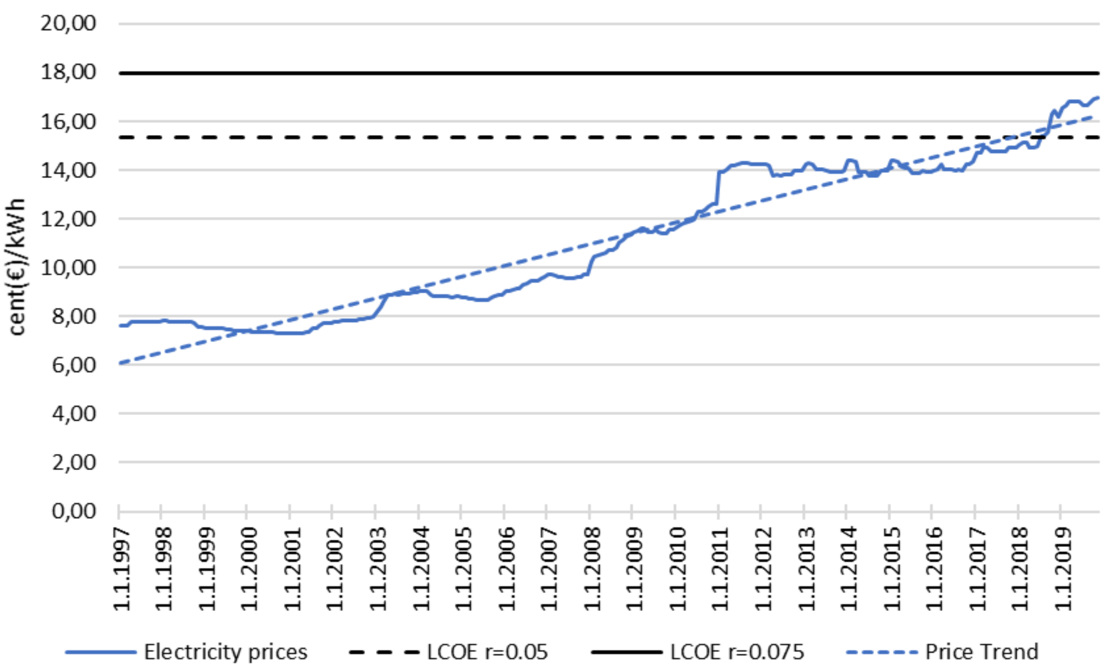

Figure 8. Consumer eletricity prices in Finland (Energiavirasto 2019.)

As the consumer prices of electricity have increased over the time period, solar power seems to have become a cost-efficient and viable method of electricity production in Helsinki. Especially, if the overall price trend continues in the future, it would be reasonable to assume that the adoption of solar panels could increase in the coming years. By investing in rooftop solar systems, residents can potentially reduce their overall cost of electricity consumption, something few would refuse. Especially buildings on the higher side of the yield/area ratio distribution could benefit from solar power adoption in the form of rooftop solar panels.

5.2 Discussion

While rooftop solar power could be an attractive investment based on the results of the optimization and the comparative electricity costs, it is good to understand the limitations of this study. Firstly, the costs of individual rooftop solar systems calculated in this study are just estimates of the true costs associated with the panel allocations. In practice, different factors such as the inclination of roofs, the height of the roofs and how difficult they are to reach would undoubtedly influence the costs arising from solar system installations. Additionally, no distinction was made between the ownership of individual roofs: private citizens could take advantage of the general tax credit or the subsidies of ARA, thus lowering their individual investment costs, whereas companies and/or the city of Helsinki might apply for the governmental energy subsidy, bringing their costs down as well.

Moreover, only one provider was used in inferring the installation costs. This was mainly due to the availability of public data on the offerings of different companies. Were multiple companies included in the linear regression, there would be need for controlling the differences in the panels used by different providers and thus additional variables would have to be introduced to the regression. When some of the providers considered had only few price examples and offerings, the reliability of the regression would quickly falter when many additional variables would be introduced with only few more observations.

Additionally, the nature of the data used raises some problems to consider when estimating costs. Firstly, when all the roofs with even a little suitable area are included in the model, some roofs might obviously be too small to cover with panels in real life. Secondly, even with a minimum area of 5 m^2, the shape of the suitable sections of some roofs might be such that they could not actually be fully covered with solar panels, usually manufactured in the shape of a rectangular. Regardless, in the model the roofs were treated as continuous objects and their suitable sections as fully realizable.

Another limitation to keep in mind is associated with the electricity yields of individual roofs. While the yields are assumed to be constant while calculating the LCOEs of the different target production levels, the electricity generation from solar panels is bound to vary from year to year due to the nature of solar power and its variability. The yields of individual buildings are also calculated assuming that the panels would be installed parallel to the roofs, regardless of inclination. As mentioned in Section 2.2, the differences in electricity production can be quite notable with optimal installation in terms of cardinal directions and inclination.

Finally, as stated before, using LCOE as the measure of cost has its limitations. As seen in the results, the mean prices obtained in this study are sensitive to the discount rate used, and in conjunction the interest rate r. Of course, as the costs of individual roofs are estimates, the LCOE as well becomes more an estimator than actual in-practice cost of the electricity produced. There is also the question what the actual level of maintenance costs M_t is, and how the costs may differ widely between locations. Some locations and systems might require only slight maintenance, thus the associated costs being less than the 3% used in this study, while in some areas where there is e.g. a lot of road dust the installations might need additional maintenance. The LCOEs calculated were also based on the optimal allocations of panels in Helsinki. A more likely scenario is a somewhat random adoption, where the optimality between the area used and electricity produced is not present.

Regardless, this study has some practical implications both for individual citizens and the city of Helsinki and can be used as a starting point for potential solar panel investments in Helsinki. For the city of Helsinki, a similar optimization model could be used with data on the publicly owned buildings and roofs, with the benefit of the city having an absolute say on the actual implementation of any allocation obtained from the optimization. Helsinki could then choose a desirable level of solar power generation and employ the model to find the most cost-efficient allocations possible. Additionally, if Helsinki wanted to further incentivize private citizens to adopt solar systems, similar LCOE calculations might be used to assess how different (monetary) incentive schemes might affect the price of electricity generated from typical solar installations.

For individuals, this study may raise awareness on the increasing cost-efficiency of solar power compared to the rising electricity prices. Similar calculations for the LCOE of individual solar systems could be used to assess the potential of citizens' own buildings or homes for solar power generation. Moreover, the data on the roofs of Helsinki used with the optimization model is readily available in map format through the website of HSY (2015). Simply calculating the expected yield/area ratio can act as a preliminary assessment whether a particular roof could be profitable with solar panels. If the ratio is on the higher side of the range discussed in Section 5.1, the roof would most likely produce cost savings during its investment cycle. Additionally, individuals might use the methods described in this study to assess the offerings of different providers, when exact quotations for solar systems are given.

6 Conclusion

This thesis focused on assessing whether solar panels on the roofs of Helsinki might be a viable power source, were a large-scale adoption to take place. A model for the optimization of panel allocation was created, where, given a production target level, an optimal set of roofs is chosen minimizing the area the panels require. The costs of individual rooftop solar installations were estimated based on the offerings of a local electricity and solar systems provider. Finally, levelized costs of electricity (LCOE) were calculated for the varying allocations and production levels. It was found that following an upward trend in the average consumer electricity prices in Finland, the levelized costs of the electricity produced by the optimal panel allocations have become competitive with the market prices. Especially private consumers who mainly use the generated electricity themselves can benefit from rooftop solar systems.

As solar power seems to be a viable source of energy on the roofs of Helsinki, the city should critically assess the potential of adding it to the current energy source mix. A good starting point would be to use the optimization model created in this study with the public rooftops in Helsinki, which could potentially decrease the current level of carbon emissions produced by the city. Given the ambitious goals of carbon-neutrality by 2035, Helsinki might also consider further incentivizing investments and raising awareness on the potential of solar power for private citizens and companies.

Regarding implications for the scientific literature, this study can be used as the starting point for future research on the viability of residential rooftop solar power. Provided that similar data is available on a particular area's roofs, a similar model could be employed to first allocate solar panels efficiently to the roofs and then assess the costs associated with the allocation. Of course, the availability of data may be a restricting factor in many locations, especially if the area under consideration is small i.e. the set of roofs is small. Still, projects utilizing for example LiDAR might be used in the future to gather datasets even in smaller areas, as discussed in Section 3.1. Additionally, it would be beneficial to understand how the costs and electricity yield of large-scale solar adoption would change if the installations on rooftops were both inclined and faced optimally. As discussed in Section 2.2, at least the yield would potentially increase notably. Still, the cost-efficiency of the systems could also decrease if the additional mounting and installation costs would outweigh the increased electricity generation.

Finally, introducing a noteworthy share of variable energy sources to any power grid will likely affect the grids' balancing and flexibility, and the electricity market prices as well. Future research should focus on the ability of Helsinki's local power grid to accommodate such an increase in variable power generation and how the electricity markets would react in terms of electricity prices of different sources. Furthermore, studying the integration costs arising from rooftop solar systems not considered in this study could provide additional information on the viability of a large-scale variable renewable energy source additions to the production mix of Helsinki's electricity infrastructure.

References

Reports and treaties

Energiavirasto (2019), “Sähkön toimitusvelvollisuus- ja siirtohintojen kehitys”, *Energiavirasto*. Available at: https://energiavirasto.fi/sahkon-hintatilastot.

European Commission (2019a), “The European Green Deal”, *European Commission*. Available at: https://eur-lex.europa.eu/legal-content/EN/TXT/?qid=1596443911913&uri=CELEX:52019DC0640#document2.

European Commission (2019b), “PV Status report 2019”, *Joint Research Centre of European Commission*. Available at: https://ec.europa.eu/jrc/sites/jrcsh/files/kjna29938enn_1.pdf.

Helsingin kaupunki (2018), “Hiilineutraali Helsinki 2035 -toimenpideohjelma”, *Helsingin kaupunki*. Available at: https://www.hel.fi/static/liitteet/kaupunkiymparisto/julkaisut/julkaisut/HNH-2035-toimenpideohjelma.pdf.

Ilmatieteenlaitos (2020) “Energialaskennan testivuodet 2020”, Available at: https://www.ilmatieteenlaitos.fi/energialaskenta-try2020.

International Energy Agency (IEA) (2020a) “Renewables 2019”, *International Energy Agency*. Available at: https://www.iea.org/reports/renewables-2019.

International Renewable Energy Agency (IRENA) (2020) “Renewable energy generation costs in 2019”, *International Renewable Energy Agency,* June 2020. Available at: https://www.irena.org/publications/2020/Jun/Renewable-Power-Costs-in-2019.

Mills, A. & Wiser, R. (2010) “Implications of Wide-Area Geographic Diversity for Short Term Variability of Solar Power”, *Ernest Orlando Lawrence Berkeley National Laboratory,* Berkeley California, September 2010.

Paris Agreement (Dec 13th, 2015) *United Nations Framework Convention on Climate Change*.

Tilastokeskus (2020a) “Sähkön ja lämmöntuotanto 2019”. Available at: https://www.stat.fi/til/salatuo/2019/salatuo_2019_2020-11-03_tie_001_fi.html.

Tilastokeskus (2020b) “Moottoriajoneuvokanta 2019”. Available at: http://www.stat.fi/til/mkan/2019/mkan_2019_2020-02-28_tie_001_fi.html#:~:text=Manner%2DSuomen%20rekisteriss%C3%A4%20oli%20vuoden,m%C3%A4%C3%A4r%C3%A4%20kasvoi%2089%20prosenttia%20edellisvuodesta.

Articles

Anvari, M., Lohmann, G., Wächter, M., Milan, P., Lorenz, E., Heinemann, D. & Reza Rahimi Tabar, M. (2016) “Short term fluctuations of wind and solar power systems”, *New Journal of Physics,* 18, Jun 2016, pp. 14.

Azadeh, A., Ghaderi, S.F. & Maghsoudi, A. (2008) “Location optimization of solar plants by an integrated hierarchical DEA PCA approach”, *Energy Policy*, 36(10), October 2008, pp. 3993-4004.

Bawazir, R.O. & Cetin, S.N. (2020) “Comprehensive overview of optimizing PV-DG allocation in power system and solar energy resource potential assessments”, *Energy Reports*, 6, Nov 2020, pp. 173-208.

Bertsch, J., Growitsch, C., Lorenczik, S. & Nagl, S. (2016) “Flexibility in Europe’s power sector – An additional requirement or an automatic complement”, *Energy Economics,* 53, Jan 2016, pp. 118-131.

Christensen, V., Ferdaña, Z. & Steenbeek, J. (2009) “Spatial optimization of protected area placement incorporating ecological, social and economical criteria”, *Ecological Modelling*, 220(19), Oct 2009, pp. 2583-2593.

Engül, H. & Theis, T.L. (2011) “An environmental impact assessment of quantum dot photovoltaics (QDPV) from raw material acquisition through use”, *Journal of Cleaner Production,* 19(1), Jan 2011, pp. 21-31.

Gadenne, D., Sharma, B., Kerrs, D. & Smith, T. (2011) “The influence of consumers’ environmental beliefs and attitudes on energy saving behaviours”, *Energy Policy,* 39(12), Dec 2011, pp. 7684-7694.

Graziano, M. & Gillingham, K. (2015) “Spatial patterns of solar photovoltaic systems adoption: The influence of neighbors and the built environment”, *Journal of Economic Geography,* 15(4), Jul 2015, pp. 815-839.

Hossain, M., Mekhilef, S., Danesh, M., Olatonomiwa, L. & Shamshirband, S. (2017), “Application of extreme learning machine for short term output power forecasting of three grid-connected PV systems", *Journal of Cleaner Production,* 167, Nov 2017, pp. 395-405.

Hirth, L., Ueckdert, F. & Edenhofer, O. (2015) "Integration costs revisited – An economic framework for wind and solar variability", *Renewable Energy,* 74, pp. 925-939.

Jacobson, M. & Delucchi, M. (2011a) "Providing all global energy with wind, water, and solar power, Part I: Technologies, energy resources, quantities and areas of infrastructure, and materials", *Energy Policy*, 39(3), Mar 2011, pp.1154-1169.

Jacobson, M. & Delucchi, M. (2011b) "Providing all global energy with wind, water, and solar power, Part II: Reliability, system and transmission costs, and policies", *Energy Policy*, 39(3), Mar 2011, pp. 1170-1190.

Lenzen, M., McBain, B., Trainer, T., Jütte, S., Rey-Lescure, O. & Huang, J. (2016) "Simulating low-carbon electricity supply for Australia", *Applied Energy*, 179(1), Oct 2016, pp. 553-564.

Lim, K.Z., Lim, K.H., Wee, X.B., Li, Y., Wang, X. (2020) "Optimal allocation of energy storage and solar photovoltaic systems with residential demand scheduling", *Applied Energy*, 269, July 2020, Article 115116.

Lund, P.D., Lindgren, J., Mikkola, J. & Salpakari, J. (2015) "Review of energy system flexibility measures to enable high levels of variable renewable electricity", *Renewable and Sustainable Energy Reviews,* 45, May 2015, pp. 785-807.

Malczewski, J. (2006) "GIS-based multicriteria decision analysis: A survey of the literature", *International Journal of Geographical Information Science,* 20(7), Feb 2014, pp. 703-726.

Maliene, V., Grigonis, V., Palevičius, V. & Griffiths, S. (2011) "Geographic information system: Old principles with new capabilities", *Urban Design International,* 16(1), Spring 2011, pp. 1-6.

Pohekar, S.D. & Ramachandran, M. (2004) "Application of multi-criteria decision making to sustainable energy planning—A review", *Renewable and Sustainable Energy Reviews,* 8(4), August 2004, pp.365-381.

Salmela, S. & Varho, V. (2006) "Consumers in the green electricity market in Finland", *Energy Policy,* 34(18), December 2006, pp. 3669-3683.

Sanchez-Lozano, J.M., García-Cascales M.S. & Lamata M.T. (2016) "Comparative TOPSIS-ELECTRE tri methods for optimal sites for photovoltaic solar farms.

Case study in Spain”, *Journal of Cleaner Production,* 127(20), July 2016, pp. 387-398.

Scarpa, R. & Willis, K. (2010) “Willingness-to-pay for renewable energy: Primary and discretionary choice of British households’ for micro-generation technologies”, *Energy Economics,* 32(1), January 2010, pp. 129-136.

Stone, J. (1998) “Geographic information systems”, *Online,* 22(3), May 1998, pp.65-70.

Strupeit, L. & Palm, A. (2016) “Overcoming barriers to renewable energy diffusion: Business models for customer-sited solar photovoltaics in Japan, Germany and the United States”, *Journal of Cleaner Production*, 123, June 2016, pp.124-136.

Sydänlammi, H. (2019) “Strategic districting for the mitigation of educational segregation: a pilot model for school district optimization in Helsinki”, Helsingin yliopisto, pro gradu.

Zhong, Q. & Tong, D. (2020) “Spatial layout optimization for solar photovoltaic (PV) panel installation”, *Renewable Energy,* 150, May 2020, pp.1-11.

News articles

CleanTechnica (2014) “Photovoltaic Dreaming 1875–1905: First Attempts At Commercializing PV”, Available at: https://cleantechnica.com/2014/12/31/photovoltaic-dreaming-first-attempts-commercializing-pv/, Accessed on 12.11.2020.

Financial Times (2019) “ Prices are down and capacity is up as solar and wind take hold”, Available at: https://www.ft.com/content/6a0f89a4-e37a-11e9-b8e0-026e07cbe5b4, Accessed on 28.10.2020.

Helsingin Sanomat (2020) “Helsinki muuttuu salakavalasti: katoilta löytyy valtavia aurinkopaneeliryhmiä”, Available at: https://www-hs-fi.libproxy.aalto.fi/kaupunki/art-2000006473505.html, Accessed on 28.10.2020.

Kauppalehti (2018) “Kaupat rakentavat nyt innokkaasti aurinkovoimaloita”, Available at: https://www-kauppalehti-fi.libproxy.aalto.fi/uutiset/kaupat-rakentavat-nyt-innokkaasti-aurinkovoimaloita/e25c4cbf-c5de-350e-9635-4fa67528f07e, Accessed on 28.10.2020.

Internet references

ARA (2020). Online. Available at: https://www.ara.fi/fi-FI/Lainat_ja_avustukset/Energiaavustus, Accessed on 11.12.2020.

GEF (2019). Online. Available at: https://static1.squarespace.com/static/5d838ff745a61007d53449d0/t/5eb25cba168203298eb5e710/1588747459325/GEF-P60+Datalehti.pdf, Accessed on 16.12.2020.

GISGeography (2020). "What is GIScience (Geographic Information Science)?". Available at: https://gisgeography.com/giscience-geographic-information-science/, Accessed on 26.11.2020.

Helen (2019). "Kaukolämpö ennätyksellisissä lukemissa - kaukolämpöön liitettiin Helsingissä enemmän tehoa kuin 40 vuoteen". Available at: https://www.helen.fi/uutiset/2019/kaukolampoliittymat, Accessed on 26.11.2020.

Helen (2020). Online. Available at: https://www.helen.fi/aurinkopaneelit/aurinkopaneelipaketit/ , Accessed on 11.12.2020.

HSY (2015) "Suitable areas for solar panels in Helsinki region", Helsingin seudun ympäristöpalvelut. Available at: https://www.hsy.fi/ymparistotieto/avoindata/avoin-data---sivut/aurinkopaneeleille-sopivat-sijainnit-paakaupunkiseudulla/, Accessed on 2.12.2020.

International Energy Agency (IEA) (2020b). Online. Available at: https://www.iea.org/data-and-statistics, Accessed on 28.10.2020.

Lumo (2020). Online. Available at: https://www.lumoenergia.fi/aurinkopaneelit/, Accessed on 16.12.2020.

Motiva (2020). Online. Available at: https://www.motiva.fi/ratkaisut/uusiutuva_energia/aurinkosahko, Accessed on 30.10.2020.

Motiva (2017). Online. Available at: https://www.motiva.fi/koti_ja_asuminen/rakentaminen/lammitysjarjestelman_valinta/lammitysmuodot/kaukolampo/lampoa_kotiin_verkosta, Accessed on 26.11.2020.

Työ- ja elinkeinoministeriö (2020). Online. Available at: https://tem.fi/energiatuki, Accessed on 11.12.2020.

United Nations (2020). Online. Available at: https://treaties.un.org/pages/ViewDetails.aspx?src=TREATY&mtdsg_no=XXVII-7-d&chapter=27&clang=_en, Accessed on 16.10.2020.

Verohallinto (2020). Online. Available at: https://www.vero.fi/en/individuals/tax-cards-and-tax-returns/income-and-deductions/Tax-credit-for-household-expenses/, Accessed on 11.12.2020.

Ympäristöministeriö (2020). Online. Available at: https://ym.fi/suomen-kansallinen-ilmastopolitiikka, Accessed on 28.10.2020.

Appendix A: The optimized allocation model

```python
"""
This model optimizes the rooftop allocation of solar panels in Helsinki.
Given a list of production targets (as percentage of total maximum of the suitable areas),
the modeler assigns either values in range [0,1] (if roofs can be partially used) or binary values
(if roofs must be wholly utilized). The modeler returns a Pandas dataframe consisting of summary statistics
from the optimal solution(s) and writes csv file(s) of the decision variable values in optimal solutions.
"""
import gurobipy as gp
import pandas as pd
from gurobipy import GRB

df = pd.read_csv("roofs_elec_area.csv", index_col=2)
df2 = df[df['areaSUM'] >= 5]

dict1 = df.transpose().to_dict('list')
dict2 = df2.transpose().to_dict('list')

keys1, area1, electricity1  = gp.multidict(dict1)
keys2, area2, electricity2 = gp.multidict(dict2)

def modeler (target, keys, area, electricity, binarity : bool = False) :

    try :

        columnList = ['index','electricityProduced','areaTaken%','roofsTaken%']
        scenarios = pd.DataFrame(columns=columnList)

        for t in target:

            m = gp.Model()

            if binarity == True :
                roofs = m.addVars(keys, vtype = GRB.BINARY)
            else :
                roofs = m.addVars(keys, lb=0, ub=1)

            areaTaken = roofs.prod(area)
            electricityProduced = roofs.prod(electricity)
            targetProduction = t*electricity.sum()

            m.setObjective(areaTaken, GRB.MINIMIZE)
            m.addConstr(electricityProduced >= targetProduction, 'c_electricityProduction')
            m.optimize()

            areaRatio = m.objVal/area.sum().getValue()
            roofRatio = roofs.sum().getValue()/len(df)

            if m.status == GRB.OPTIMAL :
                print('\nOptimal solution at %g\n' %t)
                scenarios = scenarios.append({'electricityProduced' : electricityProduced.getValue(),
                                              'areaTaken%': areaRatio,'index' : t,
                                              'roofsTaken%' : roofRatio}, ignore_index=True)
                values = {'0'+str(a) : v.X for a,v in roofs.items()}
                roofsChosen = pd.DataFrame.from_dict(values, orient = 'index')
                roofsChosen.to_csv('/Users/Juho/Downloads/roofsUsed_target_{}.csv'.format(t))
            else :
                print('\nError at %g\n' %t)

        return scenarios

    except gp.GurobiError as e:
        print('Error code ' + str(e.errno) + ': ' + str(e))

    except AttributeError:
        print('Encountered an attribute error')
```

Figure A1: Python souce code for the optimization model

Appendix B: Regression statistics on the cost function

Regression Statistics								
Multiple R	0,997585083							
R Square	0,995175998							
Adjusted R Square	0,994854397							
Standard Error	195,5051302							
Observations	17							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	118276906,4	118276906,4	3094,451216	8,57322E-19			
Residual	15	573333,8393	38222,25595					
Total	16	118850240,2						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	2666,3820	127,3876519	20,93124375	1,63008E-12	2394,861641	2937,902347	2394,861641	2937,902347
Area	165,8910	2,982159697	55,62779176	8,57322E-19	159,5346357	172,2472815	159,5346357	172,2472815

Figure A2: Regression statistics on the cost of individual solar installations

Appendix C: The random adoption model

```python
"""
A model choosing a random sample of roofs. Roofs are added until a specified target production level is reached.
"""
import pandas as pd

dataframe = pd.read_csv("roofs_elec_area.csv", index_col=2)
df = dataframe[dataframe['areaSUM'] >= 5]


def sampler(target, iterations) :

    areas = pd.Series(dtype=float)

    for i in range(iterations) :
        randomsample = pd.DataFrame(columns=df.columns)
        targetsum = target*df['ELEC'].sum()
        while randomsample['ELEC'].sum() < targetsum :
            sample = pd.DataFrame(df.sample())
            if sample.index.values not in randomsample.index.values :
                randomsample = randomsample.append(sample)
        areainstance = pd.Series(randomsample['areaSUM'].sum())
        areas = areas.append(areainstance)
    return areas.mean()/df['areaSUM'].sum()
```

Figure A3: Python souce code for the random adoption model