Diffusion of Solar PV and Battery Storage in Switzerland under Different Energy System Scenarios

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Abstract

In line with the Energy Strategy 2050, the Swiss energy system will be moving to a complete nuclear phase-out. Potentially, renewable energy technologies will replace nuclear energy in the electricity generation mix. Out of all the renewable technologies, solar power has shown the maximum potential in Switzerland. So far, solar power is responsible for a minor share in the Swiss electricity mix. But decreasing future Photovoltaic (PV) prices are expected to accelerate its adoption. However, an increase in renewable energy technologies such as solar power will result in volatility and uncertainties in the power system. The system operators will face new challenges to make the power system safe and reliable. Thus, the power system needs to be flexible enough by storing electricity and shifting demand to times of excess supply. To address this issue, battery storage systems (BSS) with solar PV are a promising solution. It helps increase self-consumption behind the meter, enabling the individuals to meet their electricity demand with PV generation and counters the diurnal cycle. Therefore, it is crucial to examine how PV and BSS will diffuse in Switzerland over the years and how policies can expedite its diffusion to ensure a smooth energy transition. For this purpose, we develop an agent-based model which can act as a powerful tool to support decision-makers in policymaking by bridging knowledge gaps. The model incorporates monetary factors like economic profitability and social factors such as environmental awareness, available information, and peer effects on the agent's decision-making. Also, the model utilizes other factors such as electricity prices, PV and battery prices, and regulations like subsidies and tax rebates to predict a realistic diffusion rate. The results indicate that the continuation of PV subsidies plays a pivotal role in the diffusion of solar PV. Further, for the adoption of BSS, an aggressive information campaign with incentives subsidizing both battery investments and PV accelerate its adoption greatly. The thesis concludes with a discussion on the influence of different individual policies on diffusion.

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Contents

List of Acronyms

ABM - Agent-Based Model
BFE - Bundesamt fur Energie
BSS - Battery Storage System
CentIv - Centralised Investments Module
DistIv - Distributed Investments Module
DSO - Distributed System Operator
EU - Eurpoean Union
FIT - Feed-in Tariff
GWh - Gigawatt hour
GWR - Eidgenossiches Gebaude- und Wohnungsregister
IRR - Internal Rate of Return
KEV - Kostendeckende Einspeisevergutung
kWp - Kilowatt peak
kWh - Kilowatt hour
MWh - Megawatt hour
O&M - Operation and Maintenance Costs
PV - Photovolataic
TWh - Terawatt hour
ZHAW - Zurcher Hochschule fur Angewandte Wissenschaften

Chapter 1

Introduction

The Sustainable Development Goals (SDGs), adopted by the United Nations General Assembly (UNGA) in 2015, has 17 SDGs with 169 targets and are intended to be achieved by 2030. Out of all SDGs, SDG-7 aims to ensure access to affordable, reliable, sustainable, and modern energy for all [1]. Later in 2016, about 197 countries signed the Paris Agreement on climate change mitigation. The agreement aims to reduce global greenhouse gas emissions and to limit the global temperature increase in this century to 2 degrees Celsius. Potentially, renewable energy can contribute to the bulk of the greenhouse gas reductions which is needed to limit the global temperature increase. Renewables can provide two-thirds of total global energy demand [2]. Therefore, renewable energy technologies and increasing energy efficiency are the core elements for a seamless transition to an energy system that is clean and sustainable.

Out of all the renewable energy technologies, solar power shows great potential and is currently leading the power sector charge. In 2018, 55% of the new renewable energy capacity installed was solar PV. After solar PV, wind power occupied 28%, followed by hydropower which was 11% of the total renewable energy installed. Therefore, achievement of the SDG-7 and Paris Agreement goals depends upon solar continuing to boom [3].

In light of the growing need for climate change mitigation, energy modeling is gaining increased importance as the energy supply sector is one of the greatest contributors to global greenhouse gas emissions, and many countries across the world are going through major energy policy changes. Therefore, energy modeling can act as a powerful tool to support decision-makers in policymaking by bridging knowledge gaps and providing facts through deep technical analysis.

Out of various modeling techniques, optimization models are well-known to achieve profound energy system analysis. The optimization models define an optimal set of technology choices to attain a specific target at minimized costs under certain constraints in its equilibrium [4]. Optimization models have many advantages. They assume perfect foresight and optimize the energy system from a social planning perspective, thus producing ideal, normative results that can lead to policy-relevant insights [5]. But there are a few limitations to this method. They are unable to represent the realistic diffusion of decentralized energy technologies as they do not account for micro-level influences and social factors.

Another approach, Agent-Based Modelling (ABM) is increasingly gaining traction to predict the diffusion of renewable technologies. ABM is a simulation technique that encapsulates system-wide characteristics from the behaviors and interactions of autonomous decision-making entities called agents. ABMs are simulations and do not optimize the system. They offer a different perspective as they incorporate the complexity of human decision-making by factoring in social processes and non-monetary influences. ABM has emerged as an important tool for many applications like urban traffic simulation, humanitarian assistance to emergency evacuations, and epidemiology. ABM has the ability to simulate a virtual world with complex systems where the many heterogeneous agents act intricately and realistically. This provides invaluable insight and predictions about the dynamics of the real-world system that it aims to emulate. The three main advantages of ABM models are their flexibility, ability to capture emergent phenomena, and the fact that it provides a natural description of the system [6]. ABMs, unlike other models, do not rely on the assumption that the system will move towards a predetermined equilibrium state. Rather, there are rules which govern the agent's behavior, and at each time step, each agent acts according to the present situation [7].

The four primary areas of application for the ABM can be summarized as follows: 1) Flows (evacuation, traffic, and customer flow management), 2) Markets (stock market, software agents, and strategic simulation) 3) Organizations (operational risk and organizational design) and 4) Diffusion (diffusion of innovation and adoption dynamics) [6]. ABM's propensity to capture convolute emergent phenomena and make realistic predictions and policy analysis based on empirical data have increased the scientific attention received by ABMs in the field of diffusion of innovation in recent years.

Various studies predict the diffusion of solar PV using an ABM. Palmer et al. [8] used an agent-based approach to model the diffusion of residential photovoltaic systems in Italy. In her study, the payback period of the investment, its environmental benefit, the household's income, and communication with other agents are the four factors that influence the agent's adoption decision. Nunez-Jimenez et al. [9] investigated the role of responsiveness in deployment policies in the diffusion of solar PV across three countries - Germany, Spain, and Switzerland using an ABM. Various researches have also used ABM in combination with other models. Grant et al. [10] combined an ABM with life cycle assessment (LCA) to simulate rooftop solar PV adoption in Los Angeles (LA) County from 2018 to 2050 and generate CO2e impact data at the societal level to compare PV and grid electricity. Zhang et al. [11] integrated a logistic regression model to a multi-agent simulation platform to predict the diffusion of solar PV in a zip code area in the USA. Araghi et al. [12] combined a discrete choice model with an ABM to predict the diffusion of PV in the Netherlands.

With an increase in solar energy, complications due to its intermittent nature arise as solar irradiation depends on the weather, environmental, and geographic factors. Severe fluctuation of solar energy also causes stability issues and capacity complications for existing transmission and distribution systems, which leads to uncertainty and instability in the grid. Potentially, using a battery storage system (BSS) with solar PV can offer a promising solution as BSS increases self-consumption and makes an individual self-reliant. Thus, ABMs have also been used to investigate how a rise in solar energy could affect the overall energy system, and if BSS could be deployed to address the volatilities, and if yes, how to address its integration challenges. Muaafa et al. [13] in their study examine if the adoption of rooftop solar panels can trigger a utility death spiral (by initiating a cycle of rising electricity prices with rising decentralized renewable penetration, thereby eroding utility revenues) using an ABM for two US cities. The model in their study uses a feedback loop between technology adoption and electricity prices. Their study underlines that a smooth diffusion of solar will provide the grid, utility companies, and government policies enough time to adapt. Alyousef et al. [14] use an ABM to forecast the diffusion of solar PV and battery adoption in Germany and their impact on the electric grid. Their study shows that increase in electricity prices results in more PV-battery adoption in Germany (better than reducing PV-battery system prices). Adepetu et al. [15] predict the PV-battery adoption in Ontario using an ABM. Zhao et al. [16] combines an ABM and system dynamics model to create a hybrid agent-based simulation to analyze the effectiveness of various policies on the diffusion of distributed PV systems while simultaneously avoiding the instability of the transition system or sharp rising of the electricity prices. Schwarz et al. [17] used an ABM to predict the diffusion of residential solar photovoltaics in California and further addresses the integration challenges associated with high shares of solar PV with battery storage and smart policy designs.

As Switzerland's energy policy moves in a new direction, a model forecasting solar and BSS diffusion can support the policymakers with profound technical analysis. To the best of our knowledge, currently, no research predicts how the solar PV and BSS will diffuse in Switzerland at the national level and regional level using an ABM. Our model is mostly inspired by the works of Schwarz et al. and Nunez-Jimenez et al. We use their framework as a reference and further develop the model and extend it to apply it for Switzerland.

The decision-making process in our model is loosely inspired by the Theory of Planned Behavior. Icek Ajzen developed the Theory of Planned Behavior as an extension to the Theory of Reasoned Action [18]. Following the Theory of Planned Behavior, a certain set of motivational factors lead to intention to perform a behavior [19]. The three main factors which affect the decision making are: 1) Attitude Towards the Behavior: This measures the agent's individual feeling, opinion, and evaluation of the behavior in question, and whether the agent believes that there will be substantial environmental gains from adopting the behavior. 2) Subjective Norms: This refers to how others in society view and influence the agent's behavior and whether they approve of their actions or not. 3) Perceived Behavioral Control: It is the belief that the individual has control over a specific action or behavior. This refers to whether the agents believe that they can successfully carry out a behavior. All these three elements together ascertain the agent's intention towards the behavior. And the positive intention results in the behavior taking place.

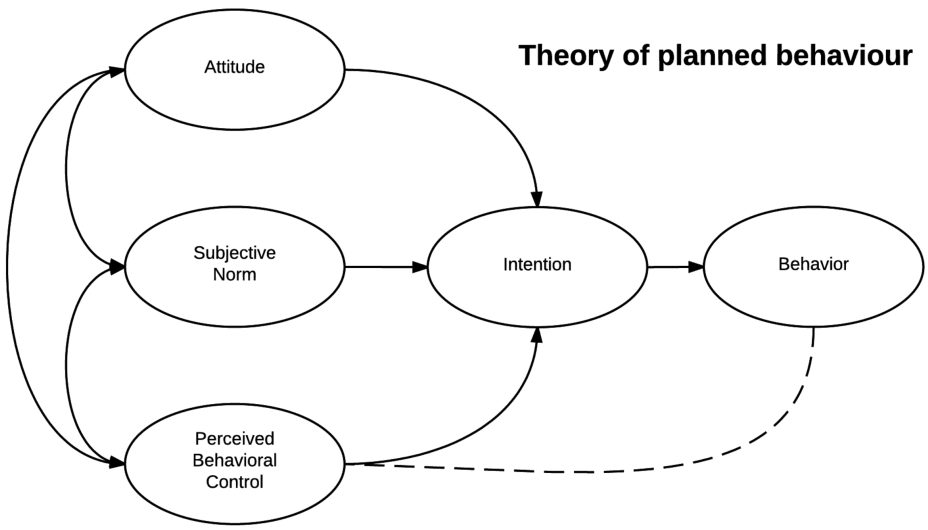


Figure 1.1: Theory of Planned Behaviour [19]

1.1 Thesis Outline

Chapter 2 is the research case and explains the motivation behind this thesis. Chapter 3 describes the method of the model, its process, and its outputs. Chapter 4 elucidates the input to the model in detail, followed by Chapter 5 which delineates the data input for policies and further spells out the policy scenarios considered in the model. Chapter 6 describes how the model is calibrated and validated. Chapter 7 summarizes the main results of both combined policy scenarios and individual policies. Chapter 8 contains the sensitivity analyses and elucidates how changing different input and assumption parameters in the model will affect the results. The last chapter concludes with the main takeaways of the thesis, the model's limitations, and lists out the scope of future work.

Chapter 2

Research Case

2.1 Swiss Energy Transition

In the wake of the Fukushima reactor disaster in 2011 and to fulfill the commitment towards climate change mitigation, Switzerland developed a new energy policy called "Energy Strategy 2050" in 2013 which was later passed as the new Federal Energy Act in 2016. The act came into force in 2018. The new Energy Act has primarily three objectives i.e. increasing energy efficiency, increasing the use of renewable energy technologies, and withdrawal of nuclear energy. Currently, nuclear energy is the source of around 35 % of the electricity in Switzerland [20]. Therefore, moving away from nuclear energy will entail profound structural changes in Switzerland's overall energy system. But, there is no clear path on how the transition to a complete nuclear phase-out will transpire. Also, there are additional questions regarding whether nuclear energy is fully substitutable, and if yes, at what pace the renewable energy technologies deployment is possible.

The energy strategy sets the "minimum" target for the electricity production from renewable energies other than hydroelectricity (PV systems, waste, and wood combustion plants, wind turbines, biogas) to 11.4 TWh per annum for 2035. The "minimum" objective for the year for 2050 is set to 24.2 TWh per annum [21]. According to their report, the majority of these renewables will probably come from PV installations. Solar power especially solar panels on the rooftop, have shown to have the maximum potential in Switzerland. Although, so far, solar power only covers a minor share of the Swiss electricity mix. In 2019, the share of solar power was 2.9% of the total electricity mix and was lower than the EU average of 4.1% [20]. Also, the diffusion of solar PV in Switzerland has been slower compared to the neighboring countries like Germany [20] (which has a 7.5 % share of solar in their electricity mix).

The solar PV diffusion has been slow due to the high installation costs in Switzerland (due to higher labor costs) and picked up only post 2011 (see Fig. 2.1). But it is estimated that with decreasing global PV panel prices, the installation prices might also drop over the next years. Policies like feed-in tariffs and investment grants also play a major role in speeding the diffusion of solar power [22]. Therefore, decreasing prices, combined with ongoing financial subsidies might kick-start the diffusion of PV.

However, with an increase in renewable energy technologies such as solar power in the Swiss electricity generation mix, system operators will face new challenges in their effort to keep the system safe and reliable. As a result, the "residual load" which must be served from the remaining generation fleet will become more and more volatile. To cope with this variability and uncertainty of renewable energy technologies, the power system needs to be flexible enough for storing electricity and shifting demand to times of excess supply.

To address this issue, BSS is a promising solution. Batteries, particularly when connected to a solar PV system, increases the self-consumption behind the meter. It enhances the household's ability to meet its electricity demand with its PV generation, and thus counters the diurnal cycle. The diffusion of battery storage, so far, is extremely low in Switzerland. High battery costs act as an impediment to the speedy adoption of BSS. Also, only a very few municipalities offer investment subsidies for battery storage. The potential realization of expected cost reductions of BSS can aid its market-wide diffusion, allowing for more residential PV integration without jeopardizing grid reliability.

Owing to these new changes, it is crucial to examine the various scenarios on how energy systems will evolve in the future. Thus, the goal of this research is to investigate to what extent the policies could affect the diffusion and ease the transition towards a nuclear-free energy system.

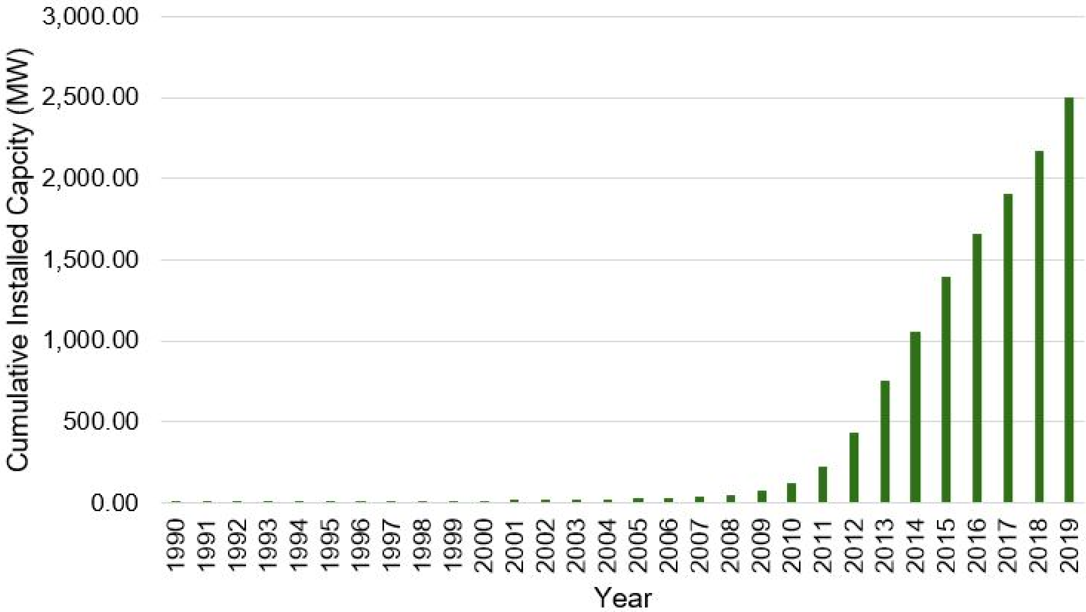


Figure 2.1: Cumulative historical solar PV adoption [23]

2.2 Evolution of Policy Support for PV in Switzerland

The Energy Act of 1998 initiated the incentives for promoting renewable energy technologies like solar PV at the national level in Switzerland. Subsequently, the policy went through many changes, and various amendments took place to keep up with new developments. Table 2.1 summarizes the evolution of the policies over the years. Further, PV systems are eligible for tax deductions on net investment and Operations & Maintenance (O&M) costs for the cantons Aargau, Bern, Basel-Landschaft, Appenzell Innerrhoden, and Appenzell Ausserrhoden from 2009, and all the other cantons from 2010. The only exception being Luzern and Graubuenden, where there are no investment tax rebates. Also, there are no policies incentivizing BSS investments in Switzerland currently.

Table 2.1: Evolution of policies for PV

Year	One-Time Remuneration	Feed-in tariff (FIT)	Source
Before 2008	Not Applicable	1) the Energy Act 1988 amended in 2005 2) fixed feed-in premium called "additional cost financing" (Finanzierungsmechanismus der Mehrkostenfinanzierung) initiated 3) all independent producers of renewable energy received around 0.15 CHF per kWh 4) this remuneration expired by December 2025 for all (except hydropower) 5) installations after January 2006 were not eligible	[24]
2008-2014	Not Applicable	1) a new feed-in tariff policy called "Cost-covering remuneration for feed-in to the electricity grid" put in place for all the installations (less than 10 MW, including photovoltaic, geothermal, hydropower, waste, biomass, or wind technology) after January 2006 2) this cost-covering feed-in tariff called "Kostendeckende Einspeisevergutung" (KEV) was provided to all renewable installations 3) but there was an overall cap regarding the budget every year for each energy technology 4) limited funds resulted in a very long waiting list especially for solar PV 5) the KEV payments initiated from 2009 for a duration of 25 years, and were not retroactive 6) there was an annual fixed degression of 8% per year	[25]

Table 2.1: Evolution of policies for PV

Year	One-Time Remuneration	Feed-in tariff (FIT)	Source
2014-2018	1) an investment subsidy (called "Einmalvergutung") was introduced in 2014 2) installations below 10 kWp (and more than 2 kWp) were only eligible for investment subsidy	1) only the installations above the size of 30 kWp were eligible for the KEV 2) the installations between 10 and 30 kWp had the option to choose between KEV and the investment subsidy 3) the fixed annual degression for feed-in tariff was removed 4) the term of the contract reduced from 25 years to 20 years 5) installations opting for investment subsidies were eligible for FIT (PV injection tariffs) by their local Distributed System Operators (DSOs)	[26]
2018-Present	1) all the installations below 100 kWp are only eligible for investment subsidies	1) the installations above 100 kWp can only opt for the KEV 2) an annual degression was reintroduced for KEV at a rate of 9% 3) the term was reduced to 15 years 4) this policy amendment also sets an end to KEV by 2020	[27]

2.3 Expected Diffusion of PV and BSS in Switzerland

Various studies predict the diffusion of renewable energy technologies like PV in Switzerland using different modeling techniques like optimization and agent-based models. The DistIv optimization module, which aims to minimize total costs and simultaneously optimize the investments and operations of a distribution system to satisfy the demand and policy targets, predicts the solar PV investment accumulation to be 28.6 GWp and PV&BSS investment to be 23.39 GWh by 2050 [28].

Paul Scherrer Institut uses the Swiss TIMES Electricity Model to calculate various energy and electricity supply scenarios and finds that the combination of flexible gas power plants, photovoltaics, and wind energy is the most economical solution for a smooth energy transition. In this scenario, the PV potential by 2050 is 9.7 TWh/annum [29].

In the report, Energy Perspectives 2050 +, the Swiss Federal Office of Energy (SFOE) forecasts a capacity of 37.5 GWp of PV installation by the year 2050, which will produce about 34 TWh of electricity annually [30].

A modeling platform, Swiss Energy Planning uses the PV utilization rate in Switzerland for every municipality and extrapolates this rate for future years to estimate the PV capacity installation. They predict that Switzerland will produce about 5.4 TWh/annum of PV electricity by 2035 [31].

Considering agent-based models focusing primarily on Switzerland, Panos & Margelou et al. [32] assess the diffusion of solar PV in Switzerland for single and two-family houses. It forecasts that about 3083 MWp of solar PV capacity will be installed by 2050 in the single and two-family houses in Switzerland. Mehta et al. [33] examined the impact of self-consumption regulation on individual and community solar PV adoption in Switzerland for one district for the city of Zurich. Their study shows that the ZEV (Zusammenschluss zum Eigenverbrauch) regulation leads to higher total adoption levels through community formations.

Chapter 3

Method

3.1 Model Overview

This section explains the purpose of the model, gives an overview of the process, and lists the entities, variables, and scales of the model.

3.1.1 Purpose of Model

The ABM aims to predict the diffusion of solar PV and BSS in Switzerland from 2021 to 2050. Further, the model evaluates different policy scenarios and explores the impact of various individual policies on the cumulative adoptions of the solar PV and BSS in Switzerland at both the national and regional levels.

3.1.2 Process Overview

Once the model initializes, the model updates the electricity demand, investment costs, O&M costs, incentives (feed-in tariff, tax rebates, subsidies), retail electricity price, and the agent's available information every year. Then the agent decides on the adoption of technology based on a two-step process (See Fig. 3.1). In the first step (called the ideation step), the agent calculates the intention for installing solar PV and BSS separately. The intention depends upon the peer effects, information available on the technology, and the agent's environmental awareness. If the intention is more than the threshold, the agent develops the idea and has the intention to adopt the technology.

In the second step, the agents having positive intention determines if the technology is economically viable or not. To evaluate this, the agent calculates the IRR that can be expected over the technology's lifetime if the agent decides to invest. If the IRR is more than the agent's discount rate, the agent adopts the technology. Additionally, to account for highly aware individuals and early adopters, the agents who have a positive intention and a high environmental awareness install the technology directly without performing an economic evaluation. When both the technology systems under consideration i.e. standalone solar PV and PV&BSS have an IRR higher than their personal discount rate, then the agent adopts the system having the higher IRR. Once the agents adopt the PV&BSS, they are outside of the adoption loop, and the agents with no system or a standalone PV system repeat this process again at every step (year) until they install a PV&BSS. Further, the model assumes an agent who adopts a solar PV will again adopt a solar PV when the PV lifetime is over during the model simulation period (2005-2050).

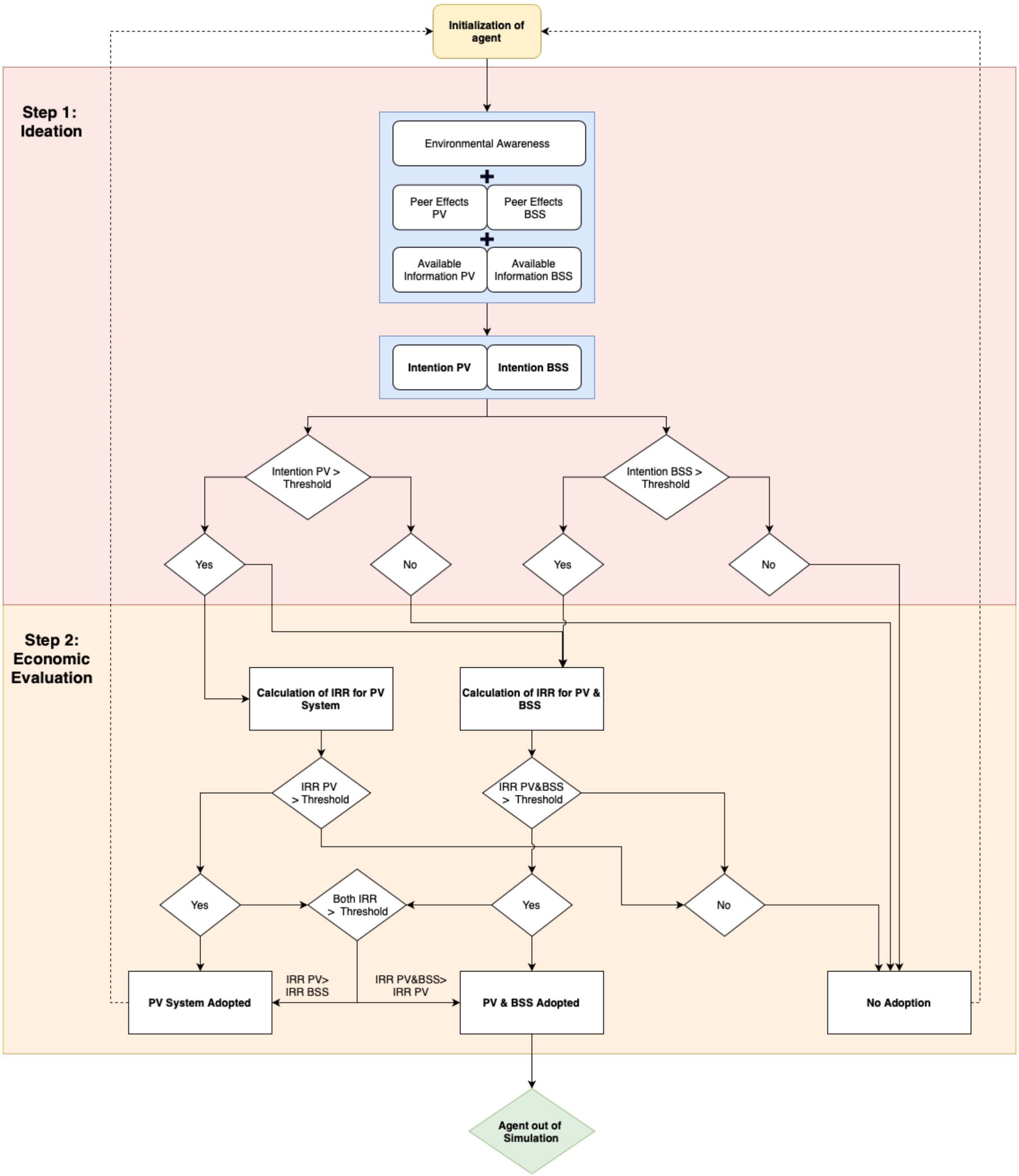


Figure 3.1: Process Overview: Dotted line represents agent going into simulation for the next year

3.1.3 Entities, State Variables and Scales

Entities

There are two types of entities in the model: the observer and the potential adopters i.e. the agents. The observer is tasked with time-keeping and updating global variables, whereas the agents are the heterogeneous and autonomous decision-making entities. The agents in the model represent the electricity consumers (buildings) of Switzerland. The model runs from the year 2005 to 2050 with yearly time steps.

State Variables

Table 3.1 summarizes the agents' variables and Table 3.2 summarizes the observers' variables.

Table 3.1: Overview of Agents' State Variables

Name	Description	Units	Type	Source
Region	Determines the region where the agent is located	-	Static	[34]
Type	Determines the building type of the agent	-	Static	[34]
Location	Defines the x and y coordinates of the agent on the grid	-	Static	[34]
Electricity Demand	Annual electricity consumption of the agent	kWh	Dynamic	[28]
Solar PV Size	The rooftop solar PV size installed by the agent	kWp	Static	[35]
Sizing Factor	The multiplication factor used by the agent to size the solar PV such that the maximum ratio between the annual solar PV generation and annual electricity demand is one	-	Static	Assumption
Environmental Awareness	Represents the agent's awareness and attitude towards solar PV and BSS	-	Static	Assumption
PV Available Information	Represents the information which is available at the agent's disposal regarding solar PV	-	Dynamic	[36]
BSS Available Information	Represents the information which is available at the agent's disposal regarding BSS	-	Dynamic	[36]
PV Neighbours	The number of agents who adopt a solar PV system and are within a 10 km radius of the agent under observation	-	Dynamic	Simulation

Table 3.1: Overview of Agents' State Variables

Name	Description	Units	Type	Source
BSS Neighbours	The number of agents who adopt a BSS and are within a 10 km radius of the agent under observation	-	Dynamic	Simulation
Self-Consumption Rate	The percentage of electricity that the system generates that the agent uses for its consumption	%	Dynamic	Simulation
Personal Discount Rate	The individual agent's capital cost for investing into solar PV and BSS	%	Static	Assumption
Electricity Demand Load Profiles	Hourly electricity demand load profile for the agent for one day of each month	kWh/h	Dynamic	[37]
Capacity Factor Profile	Hourly solar PV capacity factor profile for the agent for a randomly chosen day of each month of the year	-	Dynamic	[28]
PV Generation Profile	Hourly solar PV generation profile of the agent for a randomly chosen day of each month of the year	kWh/h	Dynamic	Simulation
Electricity Self-Consumption Profile	Hourly self consumption profile of the agent for one day of each month of the year	kWh/h	Dynamic	Simulation
Battery Storage Charging and Discharging Profile	Hourly battery charging and discharging profile of the agent for one day of each month of the year	kWh/h	Dynamic	Simulation
Electricity Feed-in Profile	Hourly profile of the surplus electricity generated by the agent for one day of each month of the year which is fed into the grid	kWh/h	Dynamic	Simulation
IRR PV	Internal rate of return for an agent investing in a standalone solar PV system	%	Dynamic	Simulation

Table 3.1: Overview of Agents' State Variables

Name	Description	Units	Type	Source
IRR PV&BSS	Internal rate of return for an agent investing in a solar PV&BSS	%	Dynamic	Simulation
IRR BSS Retrofit	Internal rate of return for an agent investing to upgrade a standalone solar PV system with BSS	%	Dynamic	Simulation
Year of PV Adoption	Year when the agent adopts the solar PV system	-	Dynamic	Simulation

Table 3.2: Overview of Observers' Variables

Name	Description	Units	Type	Source
Year	Year of the simulation	-	Dynamic	Simulation
Start Year	Initial year of the simulation	-	Static	Assumption
End Year	Final year of the Simulation	-	Static	Assumption
PV price	The price of a solar PV module including installation costs	CHF/ kWp	Dynamic	[38]
BSS price	The price of a BSS including installation costs	CHF/ kWh	Dynamic	[38]
Wholesale Electricity Price	The price at which the power plants sell the electricity to the market	CHF/ kWh	Dynamic	[28]
Grid Tariff	Tariff which the consumer pays for grid usage	CHF/ kWh	Static	[28]

Table 3.2: Overview of Observers' Variables

Name	Description	Units	Type	Source
Wholesale to Retail Price Margin	It is the the difference in price between the actual price the consumer pays, and the sum of wholesale electricity price and grid tariff	CHF/ kWh	Static	[28]
Feed-in Tariff	A fixed purchase price for electricity which the agent receives when he feeds the surplus PV electricity into the grid	CHF/ kWh	Static	[28]
One-Time Remuneration	One-time payment given by the government when investing in a solar PV system	CHF/ kWh	Dynamic	[39]
O&M Cost PV	The costs associated with operating and maintaining a solar PV system	CHF/ kWh	Dynamic	[28]
O&M Cost BSS	The costs associated with operating and maintaining a BSS	CHF/ kWh	Dynamic	[28]
Investment Tax Rebates	Tax deductions which the canton provides on the net investment costs of the PV system	%	Static	[40]
O&M Tax Rebates	Tax deductions which the canton provides on the O&M costs of the PV system	%	Static	[40]
Intention Threshold	The threshold of intention above which the agent considers to install the system and moves to the next step of economic evaluation of the said technology system	-	Static	Assumption
High Awareness Threshold PV	The threshold above which the agent is considered highly environmentally aware, and if the intention is also positive, it skips the economic evaluation step and directly adopts the solar PV system	-	Static	Calibration

Table 3.2: Overview of Observers' Variables

Name	Description	Units	Type	Source
High Awareness Threshold BSS	The threshold above which the agent is considered highly environmentally aware, and if the intention is also positive, it skips the economic evaluation step and directly adopts the solar PV&BSS	-	Static	Calibration
Ideation Step Weights	The weights of each of the components in calculation of the agents' intention	-	Static	Calibration
Peer Effect Radius	The radius within which the agents' neighbours' adoption status will have an effect on the agent under observation	-	Static	Assumption
Resizing Parameter	Determines the number of buildings each agent represents in the model	-	Static	Assumption

Scales

Running the model for every building in Switzerland would require a long simulation time. To avoid this, the model scales down all the buildings independent of the building type in the ratio of 1:1000 i.e. one agent represents 1000 buildings in our model. The agent will be a realistic representation of one building and not be cumulative of a 1000 buildings. There are a total of 2042 agents in our model. Table A.1 shows the number of agents per region. In the model, each time step refers to one year.

3.2 Modeling Process

3.2.1 Initialisation

The model initializes in the year 2005 and creates an artificial population of agents (based on the scaling). Then, it assigns every agent their variables according to the year. Out of these variables, some remain constant and some vary from one simulation run to another (due to stochasticity of inputs). Variables like region, type, and geographical coordinates remain constant for all simulation runs and scenarios. To decrease the simulation time, the model takes a 24-hourly profile for one day from every month (total of 288 hours) instead of every hour profile (8760 hours). The model is stochastic due to the randomness of some variables, as it helps to shorten simulation time and allows for a realistic representation by accounting for uncertainties and variabilities.

The following variables vary at every run: 1) Capacity Factor: To account for the variations in the sunshine within a month (cloudy day, sunny day, or rainy day), a random day of the month is chosen at every run, and the agents choose that day's capacity factor profile for every month. 2) Electricity Demand Load Profiles: The model uses a delimited normal distribution to distribute each hourly demand of the demand profile among the buildings. This is to account for various demand patterns of the buildings within a particular building type and region. 3) Environmental Awareness: The model uses a delimited normal distribution function to assign environmental awareness to each agent. 4) Personal discount rate: A delimited normal distribution function assigns every agent its discount rate. 5) Maximum PV size: A probability distribution function (generated from Sonnendach [35]) assigns every agent the maximum PV size it can install.

3.2.2 Ideation

In this first step, the agent calculates whether it has the intention to invest in the technology or not. An agent develops the intention to invest in a particular technology based on its Environmental Awareness (EA), Peer Effects (PE), and Available Information (AI) for the agent (i) at time step (t). If the weighted sum of the three parameters exceeds the threshold, agents develop the idea to adopt (see Equation 3.1). Each of the three variables is normalized and has a range between zero and one. The calibration of the model determines each variable's weights (α, β, γ).The agent develops the intention for adopting PV and BSS separately.

$$\alpha * EA_{i,t} + \beta * PE_{i,t} + \gamma * AI_t > threshold \tag{3.1}$$

Environmental Awareness (EA): Environmental awareness captures the motivation, attitude, and beliefs the agents have towards clean technologies and whether or not the agent believes that the adoption of these technologies would have a positive effect on the environment. The model assigns an awareness level for both PV and BSS between zero and one based on a truncated normal distribution of mean 0.5 and standard deviation 0.2. Also, if the agent has high environmental awareness (more than a threshold), in addition to having a positive intention, it skips the economic evaluation and directly adopts the technology.

Peer Effects (PE): The influence of social interactions on agents plays a key role in the adoption of the technology [41]. Interaction with neighboring agents who are PV and BSS adopters has a positive effect on the development of the intention of the agent under observation. The equation (see Equation 3.2, used previously in Palmer et al [8] to depict the communication utility in solar PV adoption) represents the influence of these interactions. This equation is a function of the agent's total number of neighbors ($N_{i,total}$) and the number of neighbors who have adopted PV or BSS ($N_{i,adopter}$). The rate of increase in the incentive to adopt the PV or BSS increases as the number of adopters increases in the neighborhood until a "tipping point" is reached when the number of adopters is equal to half of the total number of neighbors. Beyond this point, an increase in the number of adopters shifts from an increasing rate of incentive to a decreasing rate of incentive to adopt. An S-shaped function represents and normalizes the value of the peer effects. The model calculates the peer effects separately for solar PV and BSS. The total number of neighbors is the total number of agents present within the 10 km radius of the agent under observation. Fig. 3.2 shows the effect of the number of adopters on the value of peer effects of the agent with different neighbors.

$$PE = \frac{exp\left(\frac{N_{i,adopter} - 0.5 * N_{i,total}}{0.8}\right)}{1 + exp\left(\frac{N_{i,adopter} - 0.5 * N_{i,total}}{0.8}\right)} \tag{3.2}$$

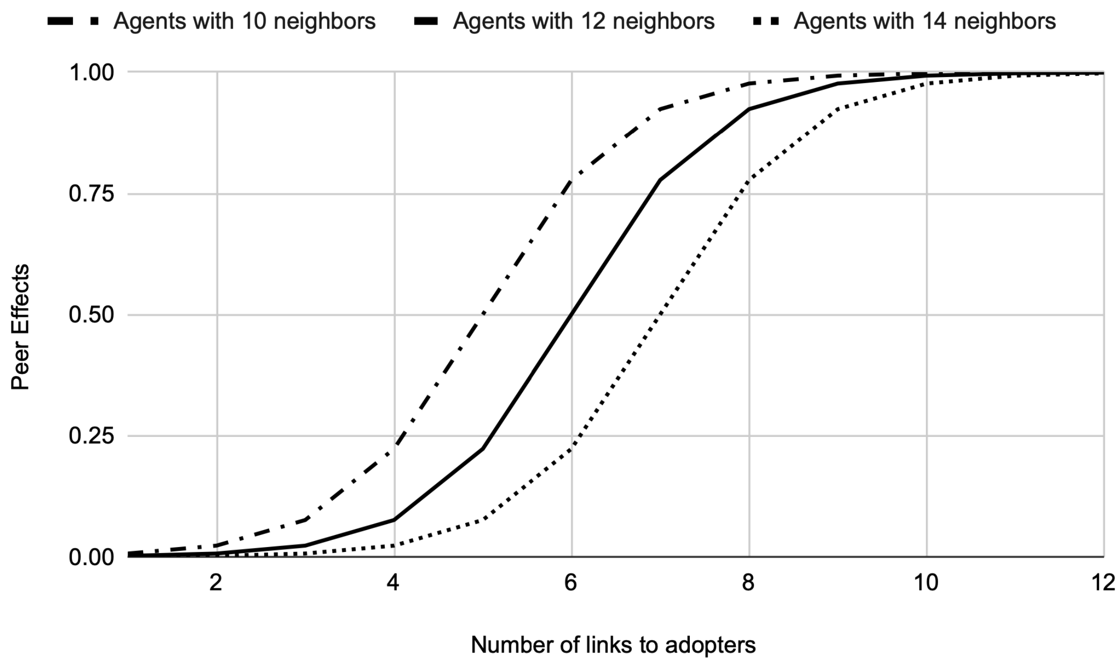


Figure 3.2: Evolution of peer effects value for an agent with different number of neighbors

Available Information(AI): Lack of information acts as a hurdle in technology adoption. News articles about the technology act as a point of source of information for the agent which helps to reduce this barrier. The model represents the available information of each agent by news articles published regarding the technology in Switzerland each year. The historically collected data about the cumulative news articles published is extrapolated for the future years by assuming an S-shaped curve until it reaches a maximum. Then the cumulative articles in each year are normalized using min-max normalization (see chapter Data).

After the initialization of the agents in the first step, the agents calculate the intention to adopt solar PV and BSS separately. The next step of the agent will depend upon the individual intention values of solar PV and BSS:

- If the intention of solar PV $>$ threshold and if the intention of BSS $<$ threshold: considers installing only a standalone solar PV system.
- If the intention of both solar PV and BSS$>$ threshold: considers installing both standalone solar PV system and PV&BSS.
- If the intention of BSS $>$ threshold and intention of solar PV $<$ threshold: no technology considered

- If the intention of BSS > threshold and agent has adopted PV: considers retrofitting battery storage system to existing solar PV system

3.2.3 Economic Evaluation

All the agents having the intention more than the threshold enter the second step of the process i.e. economic evaluation that involves the calculation of IRR of the investment for each agent i (see Equation 3.3) for time step (year) t. An IRR is the annual rate of growth an investment generates. The agent adopts the system if its IRR is more than the threshold i.e. the system is economically viable if the IRR is more than or equal to the agent's personal discount rate. The model uses IRR as a criterion for economic evaluation over the payback period because of the following reasons: 1) IRR helps to compare technologies having different lifetimes (PV [30 years] and BSS [15 years]). 2) IRR also gives an agent the advantage of knowing the actual returns of the money invested today. A 10% IRR is a good threshold [42] for a profitable investment and hence used as the mean to generate the delimited normal distribution for personal discount rates for the agents. Also, as the agent calculates the IRR over the technologies' lifetime, a higher IRR helps to factor in the expectation of a reduced payback period

$$\sum_{t=1}^{n} \frac{CF_{i,t,tech}}{(1+IRR_i)^t} - C_0 = 0 \tag{3.3}$$

$$C_0 = I_{i,0,tech} \tag{3.4}$$

Each agent, depending upon whether PV intention or both PV intention and BSS intention are higher than the threshold has three options:

Standalone PV System: To perform the IRR calculation for a standalone PV system, the agent calculates its net investment cost ($I_{i,0,pv}$) and yearly cashflows ($CF_{i,t,pv}$). The model assumes that the agent cannot anticipate the increase in electricity prices and change in electricity demand, therefore for the lifetime of solar PV, they are constant. The net investment cost is calculated using the equation 3.5. In the equation, $I_{rate,0,pv}$ is the investment rate (per kWp) for solar PV at year when the agent is considering the investment, $I_{pv\_subsidy}$ (3.6) is the one-time remuneration which comprises of a basic fee ($basic_{fee,0}$) and perfomance rate ($performance_{rate,0}$). The $I_{pv\_tax\_rebates}$ are the tax deductions received on the investment in solar PV (3.7).

$$I_{i,0,pv} = -I_{rate,0,pv} * PV_{size} + I_{pv\_subsidy} + I_{pv\_tax\_rebates} \tag{3.5}$$

$$I_{pv\_subsidy} = basic_{fee,0} + performance_{rate,0} * PV_{size} \tag{3.6}$$

$$I_{pv\_tax\_rebates} = 0.2 * (I_{rate,0,pv} * PV_{size} - I_{subsidy}) \tag{3.7}$$

The agent determines the cash flows per agent for a year by calculating the amount of electricity (out of total electricity generation from solar PV [$PV_{i,t}$]) used for self-consumption every hour for the 12 days (one day for every month, then multiplied with 30 to represent the year). The self-consumed electricity ($SC_{i,t,pv}$) in kWh multiplied with the Electricity Price $EP_{i,t}$ (CHF/kWh) determines the savings in the electricity bill. The local DSOs remunerates the excess electricity fed to the grid by paying a feed-in tariff (FIT_i, CHF/kWh) to the agent. Also, the calculation of annual cash flow includes deduction of O&M costs ($OM_{pv\_costs(i,t)}$, CHF/kWp) and addition of tax rebates ($OM_{pv\_tax\_rebates}$) received for these costs (see Eqn. 3.9). Using the above parameters, the agent calculates the cash flow using the equation 3.8.

$$CF_{i,t,pv} = SC_{i,t,pv} * EP_{i,t} + (PV_{i,t} - SC_{i,t,pv}) * FIT_i - OM_{pv\_costs(i,t)} + OM_{pv\_tax\_rebates} \quad (3.8)$$

$$OM_{pv\_tax\_rebates} = 0.077 * OM_{pv\_costs(i,t)} \quad (3.9)$$

As the PV degradation rate is assumed to be zero, the yearly cash flow is constant for the lifetime of PV. Further, combining the investment and cash flow equations mentioned above in Equation 3.3 calculates the IRR for the investment.

PV&BSS: For PV&BSS, the method to calculate IRR is the same as that of solar PV. Net investment, in this case ($I_{i,0,pvb}$), is calculated by adding the cost of the battery (two batteries, includes replacement cost added for battery after 15 years) to the net investment cost of solar PV (See Equation 3.10). Further, the agent assumes that the battery replacement costs will be 70 % of the present costs [28]. Currently, there are no subsidies or tax deductions for the BSS.

$$\begin{aligned} I_{i,0,pvb} = -I_{rate,0,pv} * PV_{size} + I_{pv\_subsidy} + I_{pv\_tax\_rebates} - I_{rate,0,battery} * \\ battery_{size} * \left(1 + \frac{0.7}{(1 + discount\_rate)^{batt\_lifetime}}\right) \end{aligned} \quad (3.10)$$

$$\begin{aligned} CF_{i,t,pvb} = (SC_{i,t,pv} + SC_{i,t,bat}) * EP_{i,t} + (PV_{i,t} - SC_{i,t,pv} - SC_{i,t,bat}) * FIT_i - \\ OM_{pv\_costs(i,t)} + OM_{pv\_tax\_rebates} - OM_{bat\_costs(i,t)} \end{aligned} \quad (3.11)$$

In PV&BSS, the battery stores the excess PV electricity generation. The amount of energy stored in the battery in that hour depends upon the PV electricity generation, electricity demand, battery charge level, battery size, and battery degradation rate. Stored electricity is later used by the agent when the PV electricity generation is not enough to cover the whole electricity demand ($SC_{i,t,bat}$). Therefore, this increases the self-consumption and leads to more electricity bill savings. As the agent does not feed all the surplus energy of the hour into the grid, it results in a decrease in revenues due to FIT. Incorporating all these changes, the agent uses 3.10 and 3.11 to calculate the IRR.

BSS Retrofit: This investment option is only valid for agents who have already installed a standalone PV system and are looking to upgrade their present system by retrofitting a BSS. The agent calculates the IRR for retrofit to see if investing in the battery can give a high return through electricity bill savings while simultaneously compensating for lower FIT revenues. The equation 3.12 calculates the net investment, and equation 3.14 calculates the yearly cash flow ($CF_{i,t,batt\_retro}$) for battery retrofit. The agent assumes that the battery depreciates linearly (See Eqn. 3.13) and adds the value left ($value_{left}$) of the battery in the net investment calculation in the case when solar PV's lifetime gets over before battery lifetime ($batt\_lifetime$).

$$I_{i,0,bat} = -I_{rate,0,battery} * battery_{size} + value_{left} \quad (3.12)$$

$$value_{left} = \frac{batt\_lifetime_{left}}{batt\_lifetime} * I_{rate,t,battery} * battery_{size} \quad (3.13)$$

$$CF_{i,t,batt\_retro} = SC_{i,t,bat} * EP_{i,t} - SC_{i,t,bat} * FIT_i - OM_{bat\_costs(i,t)} \quad (3.14)$$

3.2.4 Model Outputs

The observer in our model measures the following variables: 1) The number of agents adopting PV and BSS every year. 2) The cumulative capacity of PV and BSS installed every year. 3) The total electricity generated by PV for all agents every year. The effect of policies on these output variables helps to assess how various policy incentives and regulations can influence the adoption process.

Chapter 4

Data

During the simulations, the model uses the following data inputs to represent how the various variables evolve over the years:

4.1 Agent Classification

In the model, each agent represents 1000 buildings. The model further classifies each agent by region and type.

Region: For ease of calculation and to align with the data set available from DistIv, the 26 cantons are grouped into 20 regions. The cantons without transmission nodes are aggregated into the nearby cantons as described in Table A.2.

Building Type: Within the regions, we further classify the agents (buildings) into five types based on the use of building [43] namely residential, industrial, services, transport, and others (includes agricultural buildings). Federal Building and Housing Register (GWR [34]) provides the database for all the buildings in Switzerland with various attributes like its category, canton, location, and year of construction. The database contains in total about 2.3 million buildings. Our model only considers the existing buildings and eliminates the proposed (projected), demolished, and under-construction buildings. Further, GWR category codes classify the agents into building types (according to the classifications provided in GWR's official document "Merkmalskatalog" [34]). Table A.3 summarizes the details of category codes and their classification.

4.2 Investment Costs, O&M Costs and Future Projections

Investment Costs and O&M Costs: Based on the report [38] and [44] for solar PV and for BSS respectively, the Table 4.1 summarizes the investments and O&M Costs used in the model. The investment costs rate provided in the table also includes the costs of installation. All values are in CHF, and the prices are for the base year 2018. For historical PV Prices (before 2018), the prices were extrapolated retrospectively based on the learning curves available in the literature [45]. Fig. 4.1 shows the investment costs from 2005 to 2050.

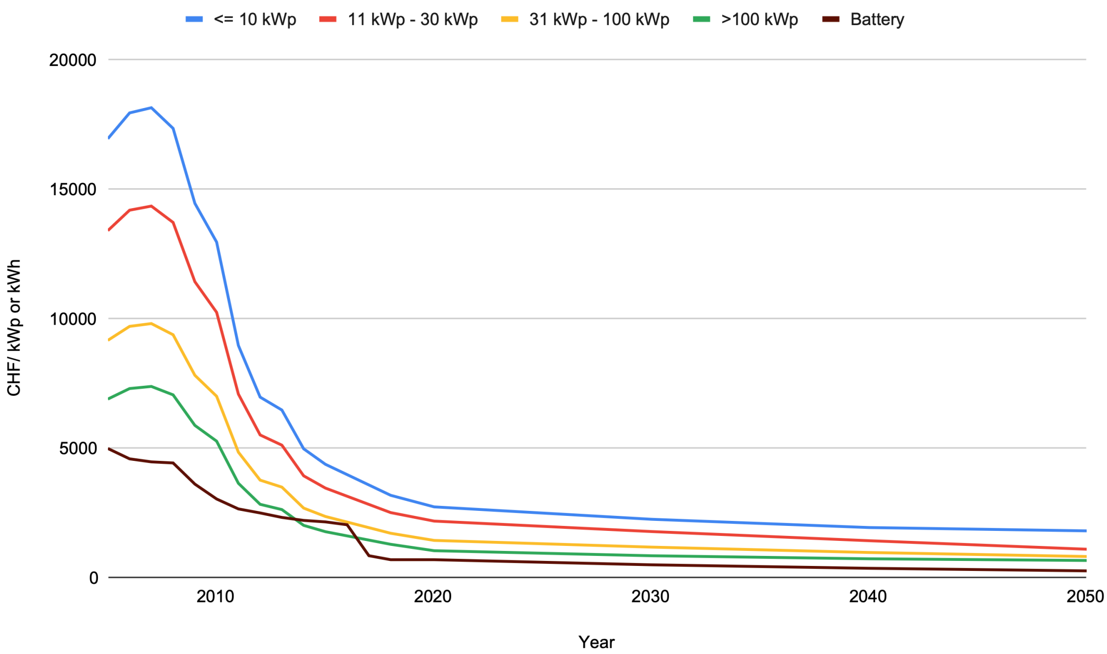


Figure 4.1: Price development of the technologies from 2005 to 2050

Table 4.1: Investment costs, O&M costs

Type	Size	Investment Cost (CHF/kWp)	O&M Cost (CHF/kWp)
PV	0 to 10 kWp	3192	3
PV	11 to 30 kWp	2525	3
PV	31 to 100 kWp	1727	3
PV	more than 100 kWp	1300	2
BSS	13.5 kWh	706 (per kWh)	2.5% of investment costs

Future Projections: For PV units and BSS for future years, the investment and O&M costs are assumed to vary as provided in the Table 4.2 and Table 4.3 respectively [38]. The tables present the future projections as a percentage of the base year (2018). Further, we assume that the costs vary linearly. Thus, linear interpolation between the years 2020, 2030, 2040, and 2050 provides the costs for every year.

Table 4.2: Investment costs: future projections

Category	2018	2020	2030	2040	2050
PV [0 to 10 kWp]	100%	86%	71%	61%	57%
PV [11 to 30 kWp]	100%	87%	71%	57%	44%
PV [31 to 100 kWp]	100%	84%	69%	57%	48%
PV [more than 100 kWp]	100%	81%	66%	57%	52%
BSS[13.5 kWh]	100%	100%	72%	53%	39%

Table 4.3: O&M costs: future projections

Category	2018	2020	2030	2040	2050
PV [0 to 10 kWp]	100%	95%	78%	68%	64%
PV[11 to 30 kWp]	100%	95%	78%	68%	64%
PV[31 to 100 kWp]	100%	95%	78%	68%	64%
PV [more than 100 kWp]	100%	95%	78%	68%	64%
BSS[13.5 kWh]	100%	100%	72%	53%	39%

4.3 Retail Electricity Prices

The retail electricity price (consumer price) comprises of three parts: 1) the wholesale electricity price, 2) the grid tariff, and 3) the wholesale-to-retail price margin. The DistIv module [28] is the source for the data for wholesale electricity price, grid tariff, and wholesale-to-retail electricity price margin. The price margin applies only to the self-consumed portion of the PV generation to offset the retail tariff faced by the consumers [28]. The price margin component accounts for the difference between the actual price paid by the consumers and the sum of wholesale electricity price and grid tariff. The price margin and grid tariff are kept constant over the years from 2005 to 2050. The wholesale electricity price varies over future years due to multiple reasons like change in demand and supply and installation of decentralized renewable technologies.

To account for the historical profiles (2005-2019) for wholesale electricity prices, the average price for the years from EPEX spot price [46] is used. Then, it is multiplied to the weighted average profile of wholesale electricity prices for the year in 2020 to get the hourly profile of the price for the historical years. The weighted profile of the wholesale electricity price is assumed to be constant from 2005 to 2019. Fig. B.1, Fig. B.2 and Fig. B.3 shows the wholesale electricity prices, grid tariff, and the wholesale-to-retail price margin over the years.

4.4 Solar PV Size and Battery Size

Sonnendach from BFE [35] combines the data from Swiss Federal Office of Energy (SFOE), Federal Office of Meteorology and Climatology: MeteoSwiss, and Federal Office of Topography: Swisstopo to estimate the total solar potential for Switzerland. It collects the data for the size and orientation of each of the individual roof areas of the buildings in Switzerland and combines it with the satellite-based solar irradiation data from MeteoSwiss to calculate the total solar potential of Switzerland. The Sonnendach database contains the roof sizes (in m^2), tilt, and object type for all the buildings in Switzerland. It assumes a module efficiency of 17 % and also assumes that installing a solar PV of 1 kWp requires an area of 6 m^2 roof area. For calculating the solar potentials from the data, we perform the following steps: 1) We drop the roofs that are less than $10m^2$ and fall under the category of Class 1 and Class 2 (very low irradiation levels of less than 1000 kWh/m^2/year). 2) Also, we remove the roofs belonging to the buildings under construction. 3) We allocate an adjustment factor depending upon the tilt and object type to each roof (see Fig B.4 and B.5). 4) Then, we multiply the roof sizes with their respective adjustment factors and divide them by 6 (1 kWp requires an area of 6 m^2) to obtain the solar potential of each roof. Further, we link this data to the GWR data. Sonnendach database contains a GWR_EGID (ID for the building in GWR) for about 80% of the roof objects. After connecting the two databases, we group them by region and type to obtain the data for roof potentials for each building of each region and each type. Out of 2.3 million buildings in GWR, we can classify about 2.04 million buildings into types. For the other 0.26 million buildings, either it was under construction or the category was not available. And out of these 2.04 million buildings, only 1.5 million buildings could be linked with Sonnedach. There are no GWR data points for some Sonnendach objects. The reasons include data gaps, the recently built buildings which are not recorded yet in GWR, and GWR data points not being a building in Sonnendach [47]. To account for the solar potential of the remaining buildings in the GWR (which could not be linked), the solar potentials are sampled randomly at every run based on a probability distribution function (generated from the dataset of the solar potential of all the buildings of each type and region). The solar potential of each region and each building type are shown in Fig. 4.2 and Fig. 4.3 respectively.

Sizing Factor for PV: The agents use a multiplication factor to decide the solar PV size to install. The model assumes that the agent chooses the size of solar PV such that it can provide a maximum of 100% of its annual electrical demand (maximum ratio between annual solar PV generation and annual electricity demand of the agent is one).

Battery Size: Based on literature [48], in our model, the ratio between PV and BSS size is 1:1 (e.g. the agent with a 5 kWp solar PV installs a 5 kWh battery).

Overview Key Solar PV and BSS Parameters: Table 4.4 lists the key parameters of PV and BSS. The battery is modeled on Tesla Powerwall 2 [49]. Further, the model assumes that the battery degrades linearly every year.

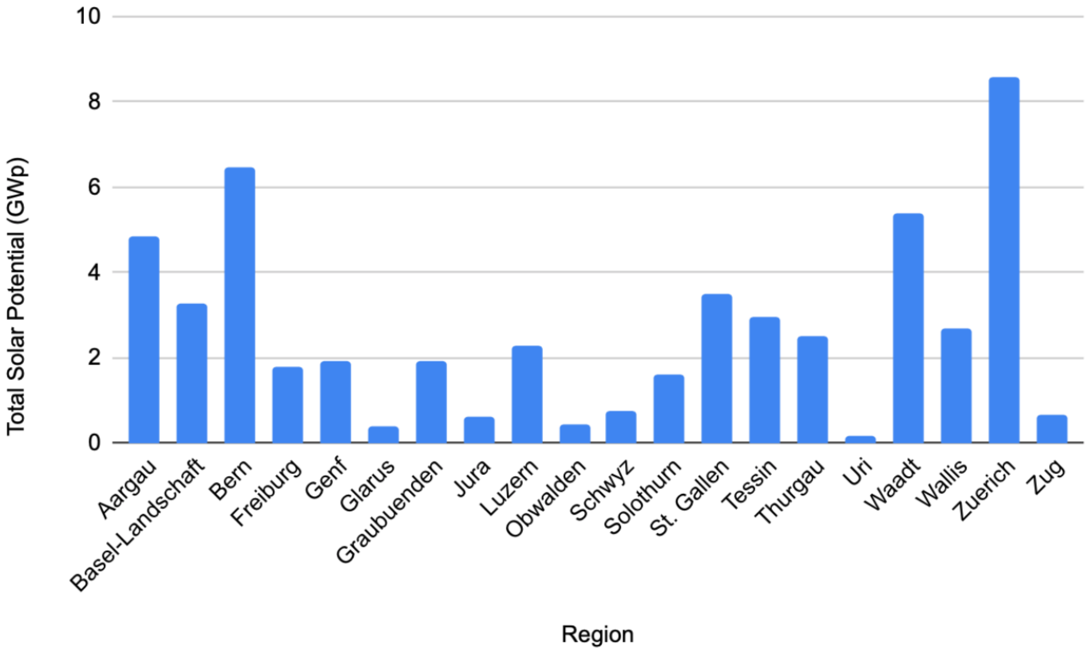


Figure 4.2: Total solar potential per region [47]

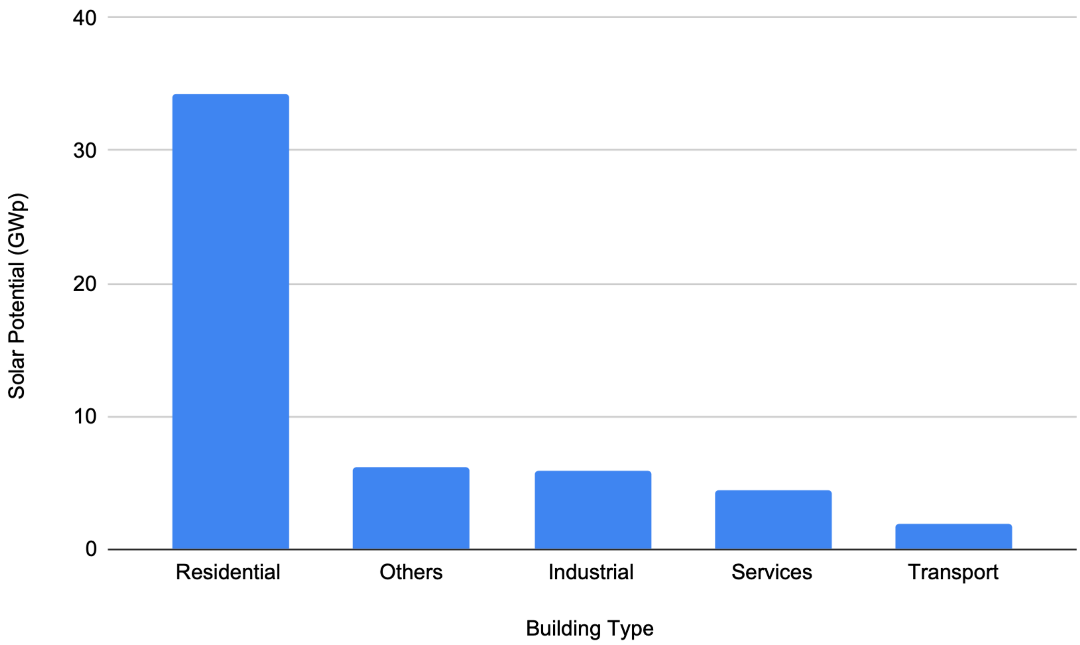


Figure 4.3: Total solar potential per building type [47]

Table 4.4: Overview of technology parameters

Technology	Lifetime	Degradation Rate
PV	30	0
BSS	15	20% in 10 years [49]

4.5 Solar PV Generation Profile

The capacity factor for PV is a ratio of the actual electrical energy output over a given period to the maximum possible electrical energy output over that period. The capacity factor profile is sourced from DistIv [28]. The capacity factor already accounts for the performance ratio of PV, and DisTiv calculates the profile for every region from irradiation values (provided by Meteoswiss [50]). The model calculates the hourly solar PV electricity generation by multiplying the PV size (in kWp) adopted by the agent with its respective capacity factor profile of one random day for each month. Fig. 4.4 shows a sample solar PV generation profile for a day. The average capacity factor for Switzerland is 0.115. Wallis has the highest average capacity factor, and St. Gallen has the lowest. Fig. 4.5 shows the average capacity factor for all the regions in Switzerland.

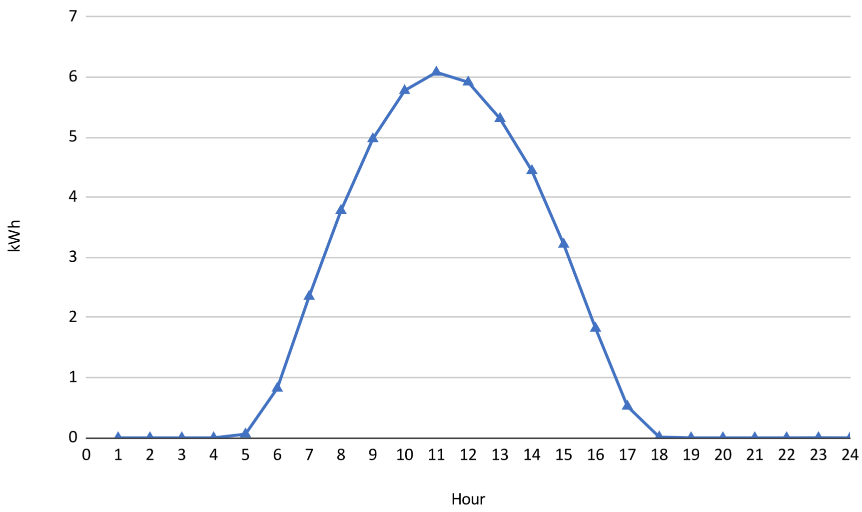


Figure 4.4: Illustration of an hourly solar PV generation profile for a sample day

4.6 Electricity Demand

The Original Transmission System Demand is also sourced from DisTiv [28] for 2020, 2030, 2040, and 2050. We assume that the values vary linearly between the decades. We obtain the values for each year between the decades by linear interpolation. The Original Transmission System Demand is equal to the national demand plus the additional generation required to meet station load, pump storage, and net exports [51]. We calculate the ratio between the original transmission system demand and the electricity demand used by end consumers from the values given in the report "Swiss Electricity Statistics 2019" [20] and further assume this ratio to be the same for all the years from 2005 to up till 2050.

For obtaining the electricity consumption for each type of building, ZHAW [43] provides detailed data regarding the electricity consumption of each canton and each building type in Switzerland for the year 2014. We assume that the electricity consumption by each building type within a canton will be in the same proportion from the year 2020 to 2050, as it was in the year 2014. We multiply the total demand by the respective ratios obtained from ZHAW to obtain the electricity demand of each sector (type of building) within a region.

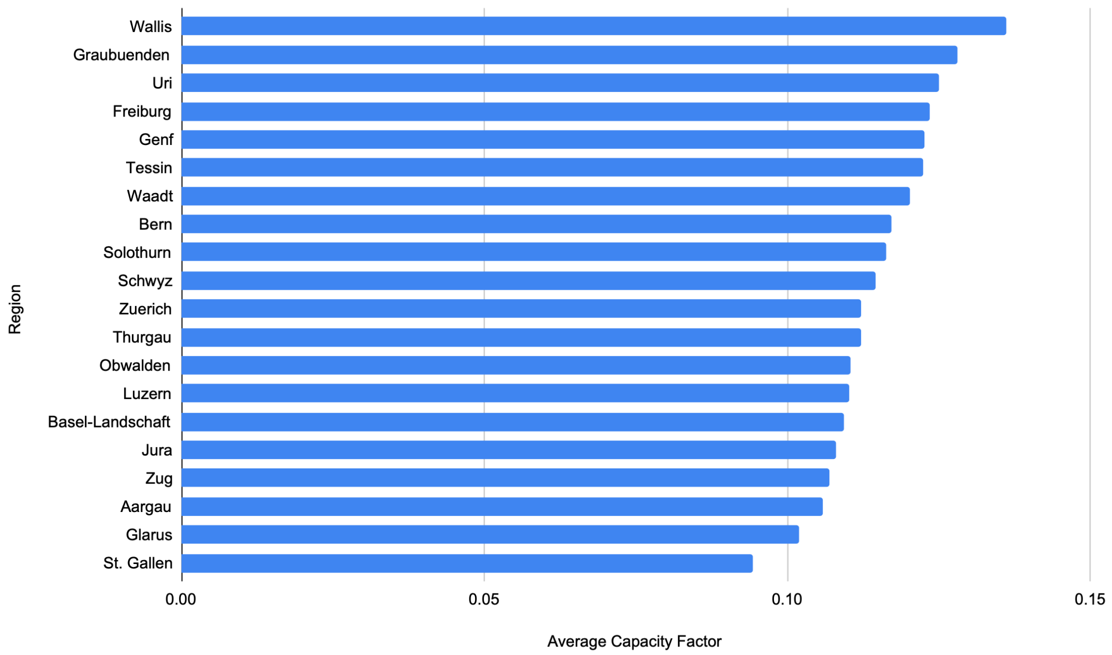


Figure 4.5: Average capacity factor of each region

To make the demand profiles more realistic, we use the standard load profiles for residential, general businesses (commercial and industrial), and agriculture (others and transport) from Stormnetz Berlin [37] for the year 2019. Then, we multiply the weighted ratio of standard load profiles and the total demand to get the load profiles of each building type. This is under the assumption that the buildings belonging to the same type will have a similar electricity demand load profile, and the electricity demand profile of buildings with similar types will be similar in both Germany and Switzerland. Fig. 4.6 shows the electricity load profiles for all the building types for one sample day.

Further, we introduce heterogeneity within the hour using a normal distribution while keeping the minimum value to be zero (μ=Mean hourly demand, $\sigma^2 = (0.2 * \mu)^2$) to account for various demand patterns within the buildings of each type and region. We create these normally distributed profiles from load profiles for each building type. Fig. 4.7 shows the addition of heterogeneity for a residential demand profile for a sample day. We further simplify the distribution of electricity demand over each agent by assuming a linear relationship between the roof size and electricity demand i.e. the demand is allotted to each building in the region proportional to the area of the roof size.

4.7 Personal Discount Rates

We assign each agent a personal discount rate from a delimited (minimum is zero) normal distribution where the mean is 10 % and the standard deviation is 20 % of the mean. This personal discount rate acts as a threshold for each agent during the economic evaluation process. The agent adopts the technology if the IRR of the investment is more than this threshold. A range of personal discount rates is chosen instead of assigning the same discount rate to every agent to factor in the heterogeneity among agents. As each agent has a distinct financial status and thus, has a different personal rate of return.

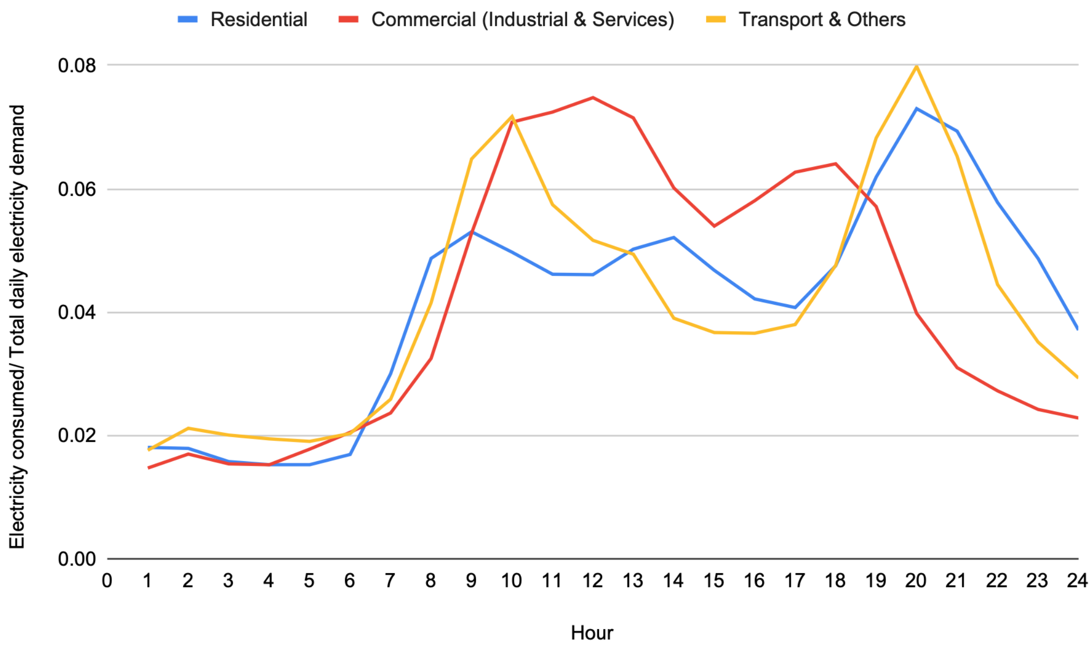


Figure 4.6: Electricity demand profiles for building types for a sample day

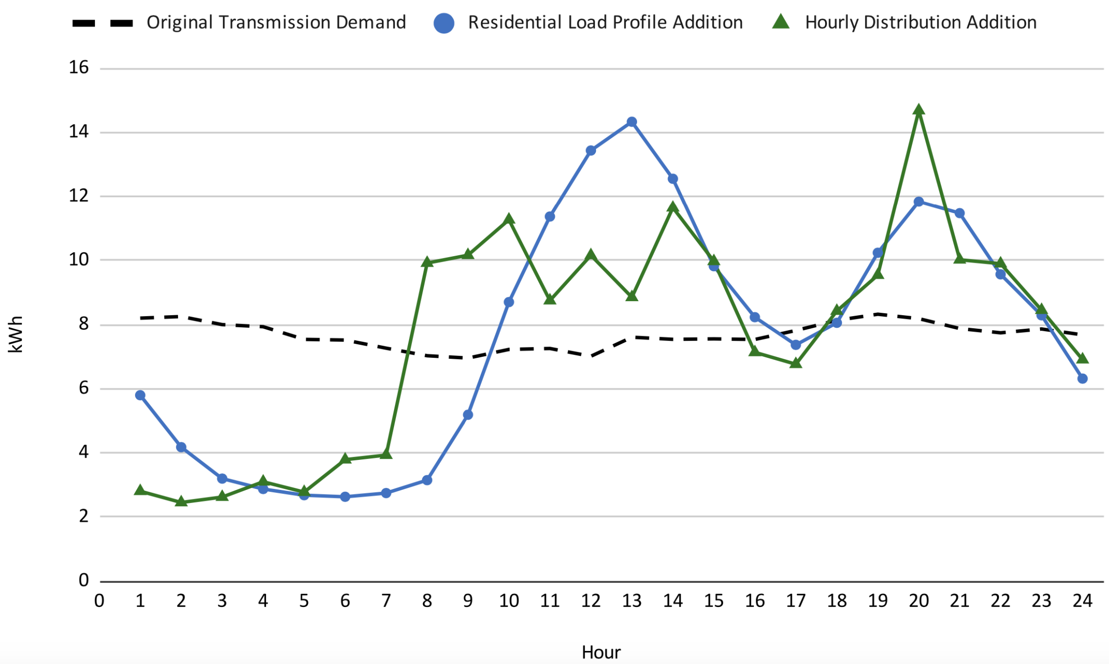
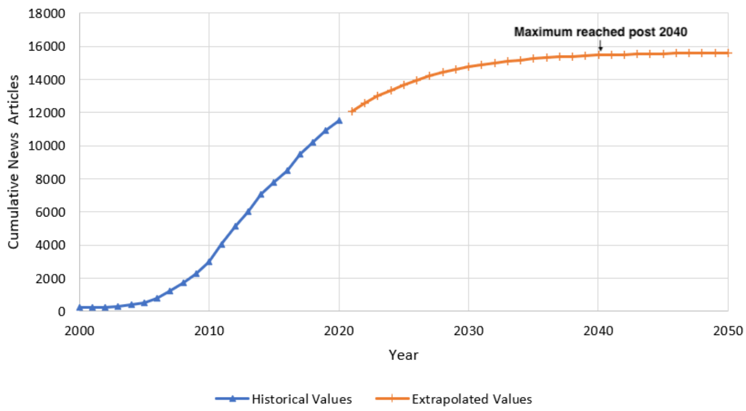


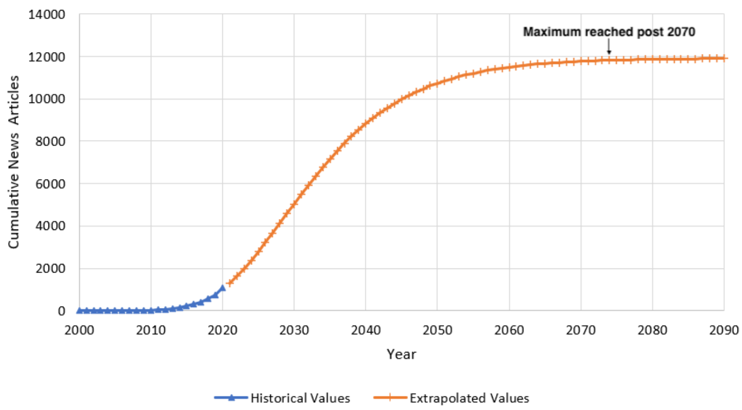
Figure 4.7: Illustration of the derivation of an hourly electricity demand profile of a household for a sample day

4.8 Available Information

The agent's information regarding a particular technology is represented in the model by the number of news articles published regarding it each year. Data about the number of news articles each year for solar PV in Switzerland were taken from Nunez-Jimenez et al. [52]. Regarding the number of articles each year for BSS in Switzerland, data was collected from from the year 2005 to 2020 from an online database [36]. The keywords used for the search were: 1) For solar PV - "solar photovoltaics" OR "solar PV" OR "photovoltaic" OR "sonnenenergie" OR "sonnenkraft" OR "solarenergie" [52]. 2) For BSS - "Battery" and "Storage" and "Solar" and "Switzerland". The number of articles published each year according to database are shown in Table A.4. Further, we assume that the available information regarding a technology (cumulative news articles) follows an S-shaped curve and reaches a maximum at some point. Beyond this point, the increase in yearly news articles becomes very low and has a negligible additional impact on agent's available information. Following the trend of historical numbers of cumulative news articles for both solar PV and BSS up till 2016 and 2020 respectively, we extrapolate the data assuming an S-shaped curve until it reaches a maximum (See Fig 4.8). Then the data is normalized by min-max normalization (minimum being zero) for every year.



(a) Solar PV



(b) BSS

Figure 4.8: Cumulative news articles over the years Switzerland

Chapter 5

Policy Scenarios

5.1 Modelling Switzerland's Historical FIT Policy

As explained in Chapter 2, the Swiss policymakers had imposed an annual cap on the funding of KEV in Switzerland between 2009 to 2018 for solar PV. This cap resulted in enormous waiting lists as the number of installations that could receive KEV every year was limited [53]. Therefore, every person installing a solar PV would not immediately receive the incentives and would have to wait until a positive decision is received. In reality, the agents could submit an application for the feed-in tariff before or after installing a solar PV system, but in the model, we assume that the agent cannot delay its decision or strategize. So the agent will apply for the feed-in tariff (KEV) in the same year it installs the solar PV. According to the policy, the feed-in tariff is granted at the moment of installation, and the payments are not retrospective. For example, if the agent applied in 2011 and had to wait three years until it receives a positive decision, he/she will receive the payments from 2014, and the waiting time is subtracted from the feed-in tariff contract.

To represent this historical policy scenario for Switzerland, the agents estimate a waiting period in the model when evaluating the investment economically. Since agents do not have perfect information, the waiting period is assumed to linearly increase every year from 2009 (0) to 2014 (5 years), and then it is constant till 2019 (as one-time remuneration subsidy was introduced to reduce the pressure on the waiting list, also Pronovo 2015 [53] report mentions a waiting period of 5 years). The model assumes a conservative waiting time for the agents despite huge waiting lists because the number of registrations for solar PV increased every year [53]. This signifies that there was a positive public opinion regarding the KEV payments and that the agents were more likely to have an optimistic approach, and assume lower waiting periods while making a decision regarding the investment.

5.2 Subsidies PV: Input

The section describes the inputs for FIT, one-time remuneration and tax rebates for solar PV in the model.

5.2.1 Feed-In-Tariff and One-Time Remuneration:

After 2019, KEV was discontinued, but the agents are eligible for PV injection tariff (FIT) (see Fig. B.6) provided by the corresponding DSOs. This FIT is constant in the model for the whole simulation time.

From 2014, an investment subsidy (called "Einmalverguetung") was introduced for projects below 30 kWp and later extended to all installations below 100 kWp in 2018. This one-time remuneration consisted of a basic fee and a performance rate (per kWp). Further, we assume that the investment subsidy in 2030 falls linearly every year to 80 % of the 2020 level [39] and discontinues from 2031.

5.2.2 Tax Deductions:

From 2010, the model considers that agents are eligible to avail a tax rebate [40] of 7.7% of the O&M costs, and 20% of the net investment costs (excluding investment subsidy) [28]. All regions are eligible for the tax rebates till 2050 except Luzern and Graubuenden, where investment cost tax rebate is not present due to regional regulations. The percentage of tax rebates assumed are simplifications of the complicated tax rebates in reality (the number varies depending on the region, the type of the building, and income).

5.3 Policy Scenarios Assessed

The model considers five major policy scenarios with various policy instruments to examine how it influences the adoption rates and cumulative adoptions of PV and BSS in Switzerland. Different types of policy instruments affect the adoption process in the model at different stages. Monetary policies like subsidies and tax rebates affect the adoption at the economic evaluation stage. They affect the profitability of investment for the agent, thus, influencing the adoption decision. On the other hand, non-monetary policies like information campaigns and awareness drives impact the adoption process at the ideation step. These policies increase the number of agents that develop the intention to adopt the technology. Thus, more agents consider adopting the technology and move towards the second step. The five policies assessed in the model are:

- **Business As Usual (BAU):** The business as usual case consists of only the present policies in Switzerland. It includes a subsidy called one-time remuneration for PV till 2030. The subsidy FIT remunerates the excess electricity fed to the grid at an average rate of 8.8 Rp./kWh, and the rate remains constant from 2021 to 2051. Also, PV installations are eligible for tax rebates on investment and O&M costs. In this scenario, there are no incentives and tax rebates for BSS.

- **Weak Policy:** This policy scenario discontinues all the incentives for PV from 2021.

- **Strong Policy (Solar PV friendly):** To incentivize solar PV adoption, the one-time remuneration continues after 2031 till 2050. The subsidy rate is kept constant from 2031 to 2050 (fixed at the rate in 2031). Also, to further incentivize PV adoption, the FIT rate increases by 50 % from 2021.

- **Strong Policy (BSS friendly):** This scenario uses a non-monetary policy like an aggressive information campaign to increase the available information of the agents from 2021 to 2040 by 35% (From 2040, available information is 100%). Also, the battery is eligible to receive a one-time subsidy of 30% on the investment costs from 2021. Further, batteries become entitled to tax rebates on investment and O&M costs at a similar rate as applicable for solar PV from 2021.

- **Strongest Policy:** This policy scenario combines both the instruments of strong policy (PV friendly) and strong policy (BSS friendly).

Table 5.1 summarizes the five policy scenarios and the instruments entailing each policy scenario.

Table 5.1: Policy Scenarios

Policy Scenarios	FIT	One-Time Remuneration PV	Tax Rebates PV	One-Time Remuneration BSS	Tax Rebates BSS	Information Campaign BSS
Business as Usual (BAU)	Average: 8.8 Rp./kWh	Basic fee : 1100 CHF; Perfomance Rate: 380 CHF/ kWp (<30 kWp); 330 CHF/ kWp (>100 kWp), Policy phase-out in 2030	7.7% on O&M costs and 20% on net investment costs	No	No	No
Weak	No	No	No	BAU	BAU	BAU
Strong: PV Friendly	+ 50% from 2021: Average 13.2 Rp./kWh	Continued till 2050, no phase-out	BAU	BAU	BAU	BAU
Strong: BSS Friendly	BAU	BAU	BAU	30% subsidy on investment costs from 2021	7.7% on O&M costs and 20% on net investment costs from 2021	Increase in AI every year by 35%, reaches maximum by 2040
Strongest	+ 50% from 2021: Average 13.2 Rp./kWh	Continued till 2050, no phase-out	BAU	30% subsidy on investment costs from 2021	7.7% on O&M costs and 20% on net investment costs from 2021	Increase in AI every year by 35%, reaches maximum by 2040

Chapter 6

Model Calibration and Validation

We calibrate the model by varying the weights of environmental awareness, peer effects, available information, and awareness threshold (for highly environmentally aware individuals). This is to evaluate the weights and threshold that produce the results which are the closest to the historical cumulative adoption in Switzerland.

6.1 PV Calibration

To avoid long simulation times and runs, the calibration for solar PV adoption takes place through three steps in the model. In the first step, the weights of environmental awareness, peer effects, and available information are varied from 0 to 1 in steps of 0.1. The weight of the awareness threshold varies from 0.8 to 0.95 in steps of 0.05. For each set of combinations of weights, ten runs are executed in the model, giving a total of 40,000 runs. The method of the least squares (See Eqn. 6.1) determines which combination of weights c would provide the best fit and least deviation (least value of L). Further, the calculation R^2 [54] determines how close the data fits the historical curve.

$$L = \sum_{t=2005}^{t=2019} (PV\_cumulative\_adoption_{model,t,c} - PV\_cumulative\_adoption_{historic,t})^2 \quad (6.1)$$

After the first step of calibration, the weights having the smallest value of L were peer effects: 0.1, environmental awareness: 0.5, available information: 0.2, and awareness threshold: 0.8. To have a better fit and further minimize deviation, further simulations were run by varying the peer effects, available information, and environmental awareness, with a step of 0.01 for the range 0.1 to 0.2, 0.1 to 0.2, and 0.4 to 0.5 respectively (a total of 10,000 runs). After the second step, the weights having the minimum value of L were peer effects: 0.17, environmental awareness: 0.5, and available information: 0.19. The peer effects show the lowest effect on adoption.

In our model, 100 runs give a deterministic output. But to decrease the simulation time, the initial steps of calibration were done with ten runs. In the next step, to get the model calibrated better, it was necessary to run the simulations for 100 runs. Therefore, for the third step, the peer effects were kept constant (since they had minimal impact), and the other two parameters environmental awareness and available information were varied in steps of 0.01 from 0.48 to 0.52 and 0.18 to 0.22 respectively (a total of 2500 runs).

After completing the third step, the weights having a minimum value of L for PV are 0.17 for peer effects, 0.21 for available information, and 0.49 for environmental awareness (See Fig. 6.1). The R^2 value for these weights is 0.997 showing the calibrated curve is almost a perfect fit with the historical adoption curve.

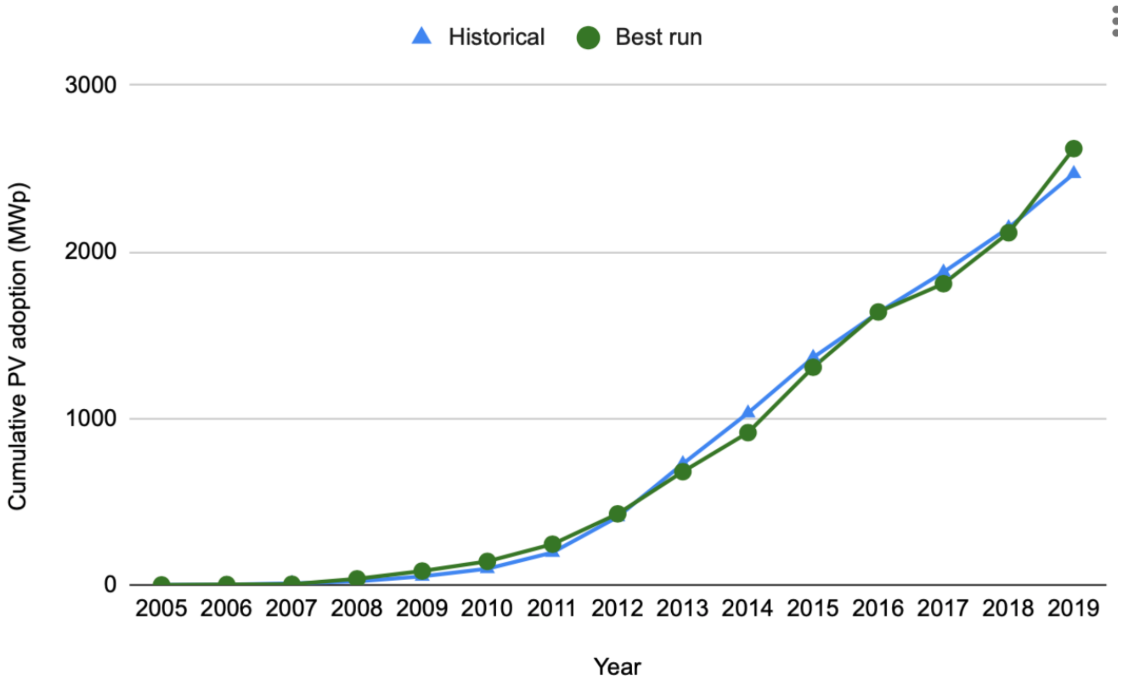


Figure 6.1: Model calibration PV

6.2 BSS Calibration

BSS is an emerging technology and has not yet gained much traction in Switzerland. Therefore, there is insufficient data to use the historical deployment of BSS to calibrate the model exhaustively. The battery storage capacity for Switzerland is only available from 2016 to 2019 in the reports 'Markterhebung Sonnenenergie 2017, 2018 and 2019' [55]. Calibrating solar PV with historical deployment calculates the extent of influence of each of the social factors i.e. peer effects, available information, and environmental awareness for the market of Switzerland. Also, initially, as the battery is not very profitable, so only the highly aware agents who leapfrog the profitability calculations will adopt PV&BSS. Therefore, we assume that the factors peer effects and available information will have the same impact on the diffusion of BSS as they would have on PV diffusion in Switzerland. To further fine-tune the calibration for BSS, we vary the environmental awareness in steps of 0.01 from 0.45 to 0.5 and the threshold from 0.8 to 0.95 in steps of 0.05. We run each combination for 100 runs to get a deterministic output. The final weights for BSS with the least-squares are 0.17 for peer effects, 0.21 for available information, 0.5 for environmental awareness, and the awareness threshold is 0.95 (See Figure. 6.2). The R^2 value for these weights is 0.93.

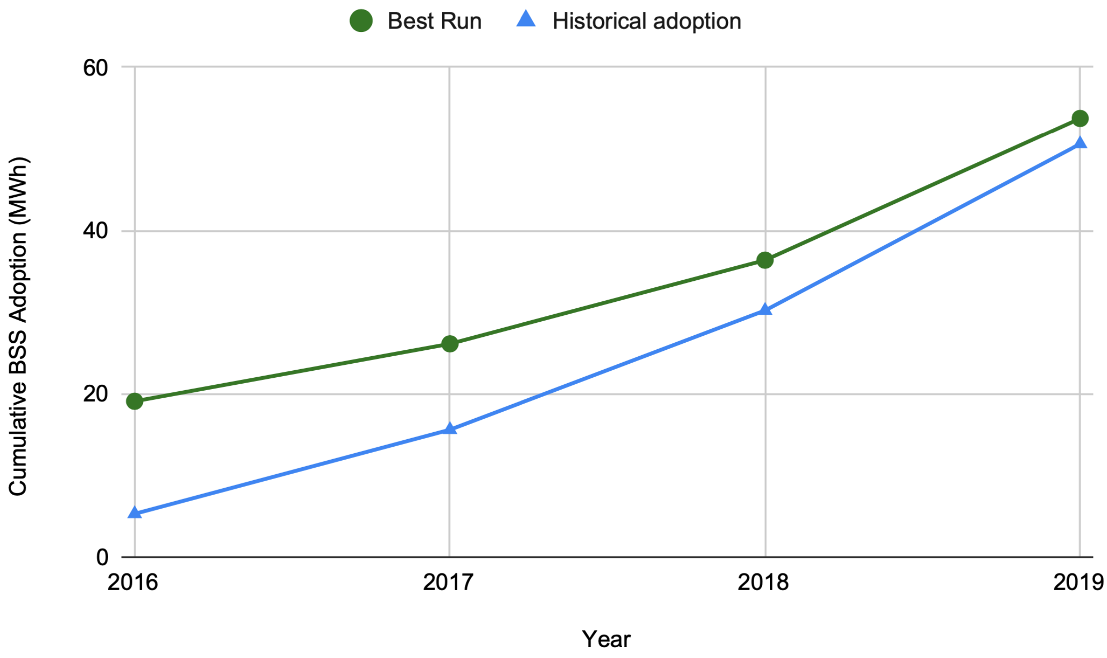
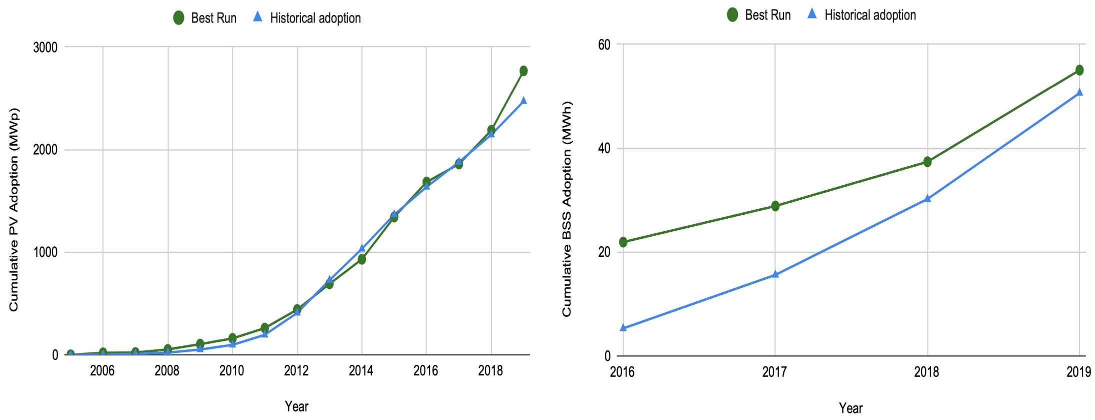


Figure 6.2: BSS: calibration

6.3 Realistic Calibration Weights to Test Policy Scenarios

The previously mentioned weights show the best fit for the historical curve and replicate the historical adoption well, but this does not guarantee that this choice of weights and threshold is fully representative of the underlying processes that drive the decision-making [56]. So to achieve a more realistic fit, and examine the policy scenarios better (so that the limited number of agents which have a positive intention does not hinder the exhaustive policy analysis), we vary the peer effects from 0.17 to 0.5 until the PV cumulative adoption of 2019 deviates by a maximum of 10 %. The peer effects have the least weight in the best fit curve and are varied because of the following reasons: 1) In literature, peer effects show a significant contribution to the formation of agents' intention. Palmer et al. [8], and Pearce et al. [57] show peer effects to be crucial in the market of Italy and the UK. For Switzerland, Nunez-Jimenez et al. [9], and Panos et al. [32] also show high weights of peer effects. 2) The model has a strong assumption that all the weights remain constant throughout the simulation. Although, this does not reflect the reality as environmental awareness and preferences are dynamic and can change over time. It is expected that over the years, environmental awareness among agents increases. A higher weight of peer effects favors a higher number of agents developing a positive intention in later years, and when more neighbors adopt a technology, the awareness also increases simultaneously. Therefore, we assume that the peer effects' function acts as a proxy for the increasing environmental awareness over the years.

The weight of peer effects in the realistic fit curve is 0.43. The new R^2 value with the realistic fit for PV is 0.994 and for BSS is 0.91. This value is a decrease of approximately around 0.3% and 0.2% from the R^2 value of the best fit case which is an acceptable deviation to use realistic fit weights instead of best-fit weights for analysis. Fig. 6.3 shows the realistic fit adoption curve with the historical adoption curve for PV and BSS. The realistic fit curve helps to fully assess the extent of influence the policies and subsidies can exert on the adoption of PV and BSS when a reasonable number of agents have a positive intention to adopt the technology.



(a) Solar PV (b) BSS

Figure 6.3: Model calibration for policy scenario analysis

6.4 Validation

We validate the model by comparing the cumulative adoption of PV in 2020, average PV sizes installed per type of building, the self-consumption rate of PV systems, and the self-consumption rate of PV&BSS with the values in the literature.

Table 6.1 summarizes the values of these parameters when the model runs with best-fit weights and realistic fit weights and further compares these with the values in the literature. The realistic fit (+12% from the value in literature) gives more installation in 2020 than the best-fit case (+6% from the value in literature). Other parameters for both the cases match well with the values in the literature.

We further validate the model at the regional level to see whether the adoption per region in the model (using realistic fit weights) follows a pattern similar to the historical adoption of PV per region. The data from the Pronovo report [58] contains the number of PV adoptions registered with them (the PV installations that availed the subsidy). We compare the share of adoption per region in the report to the share of adoption per region in the model (as shown in the figure 6.4). We further compare these two values to the share of the total number of agents in a region (out of the total agent population in Switzerland). The model's regional adoption shows a similar trend to the regional adoption obtained from the Pronovo report. It should be noted that the data from Pronovo does not represent the whole PV adoption of Switzerland (as all the PV installations are not registered with Pronovo). Therefore, there is some difference between the share of adoptions in the report and the model for regions like Luzern, Tessin, Solothurn, Freiburg, and St.Gallen, but this might be due to the data gaps. Also, we observe that the PV adoption is not directly proportional to the share of the population of the agents in the region. For example, Bern has the highest share of PV adoption in both the model and the Pronovo report despite not having the largest population or solar potential. Similarly, Waadt and Freiburg have a higher PV adoption share than Zuerich in both the model and data, despite Zuerich having a larger population and higher solar potential.

Table 6.1: Validation

Description	Unit	Simulation Value (Best Fit)	Simulation Value (Realistic Fit)	Value in Literature	Source
Cumulative PV Installation 2020	MWp	3100.5	3281.7	2929.75	[59]
Annual PV Installed 2020	MWp	457.5	513.2	430	[59]
Average Self-Consumption Rate PV	%	44.87	44.83	39	[60]
Average Self-Consumption Rate PV&BSS	%	65.16	65.08	55-69	[61]
PV Average Size: Residential	kWp	9.23	9.23	10.98/9.3	[55]/[53]
PV Average Size: Industrial	kWp	108.12	108.11	108.98	[55]
PV Average Size: Services	kWp	65.19	65.19	69.15	[55]

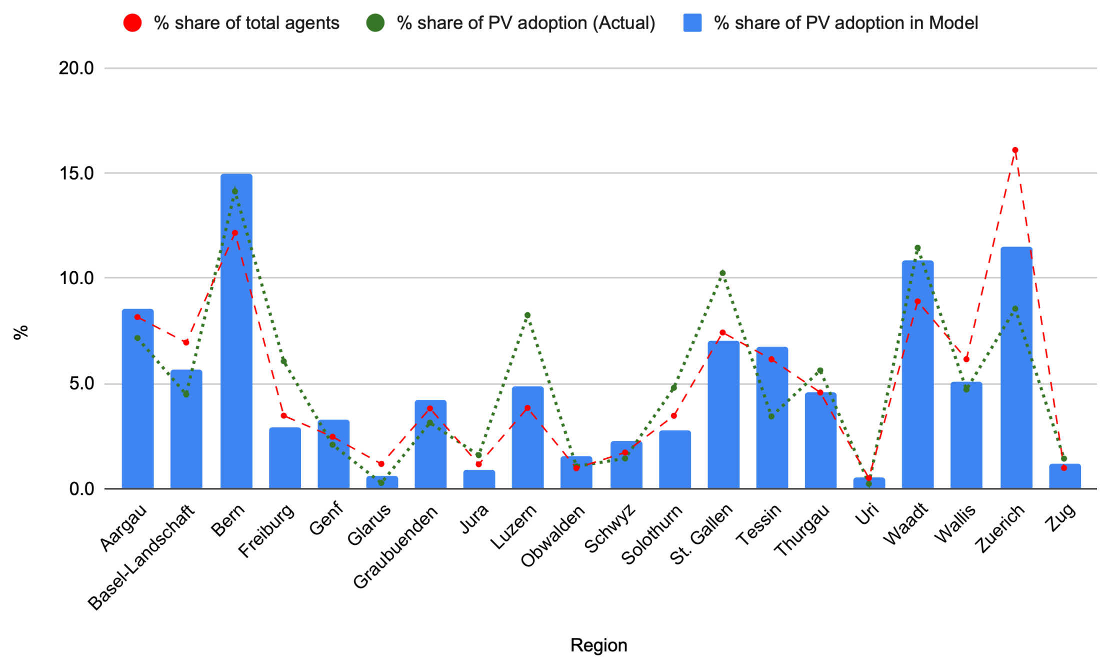


Figure 6.4: Model validation (regional adoption)

Chapter 7

Results

7.1 Forecast of Cumulative Adoption by 2050

The model is run from 2005 to 2050 with the weights of the realistic run (see model calibration) to see how PV and BSS diffuse by 2050. The PV adoption is about 17.6 GWp (See Fig.7.1) and the BSS adoption is about 6.9 GWh by 2050. The percentage of agents adopting PV and BSS are 61% and 31% respectively. PV generates about 356 TWh of electricity from 2021 to 2050, out of which about 160 TWh is self-consumed. In the case of PV, the adoption rate increases till 2030. It drops after 2031 due to the ceasing of the one-time remuneration subsidy. BSS adoption picks only after 2035 due to an increase in intention and a decrease in battery prices. The adoption rate for BSS reaches a maximum at 2040, after that adoption rate of BSS slows down due to the lower adoption of PV post-2040.

Out of all the building types, residential buildings have the highest adoption for both solar PV and BSS (See Fig. 7.2) followed by industrial and services' buildings. In Switzerland, residential buildings occupy about 65% of the total solar potential. Transport and other buildings have the lowest adoption of both PV and BSS.

At the regional level, Bern has the highest cumulative PV and BSS adoption by 2050 (See Fig. 7.3), followed by Waadt and Zurich. Zug, Glarus, and Uri have the lowest adoption of both PV and BSS as these regions have the lowest total solar potential in Switzerland.

Regions like Freiburg, Jura, and Graubuenden have the highest percentage of agents adopting PV (See Fig. 7.4). Whereas Uri, Graubuenden, and Jura have the highest percentage of agents adopting BSS. High solar irradiation and high FIT rates contribute to having a high percentage of PV adopters in Freiburg. High electricity prices and high FIT rates (higher than average) contribute to the higher diffusion of PV among agents in the region of Jura. Whereas high solar irradiation and high electricity prices increase the diffusion of both PV and BSS, and high FIT rates contribute to the higher diffusion of PV in the regions of Graubuenden and Uri. Zuerich and Basel-Landschaft have the lowest percentage of agents adopting for both PV and BSS. Zuerich and Basel-Landschaft have the lowest FIT rates in Switzerland and low electricity prices. These factors result in low cash flows making the technology not profitable enough for high diffusion.

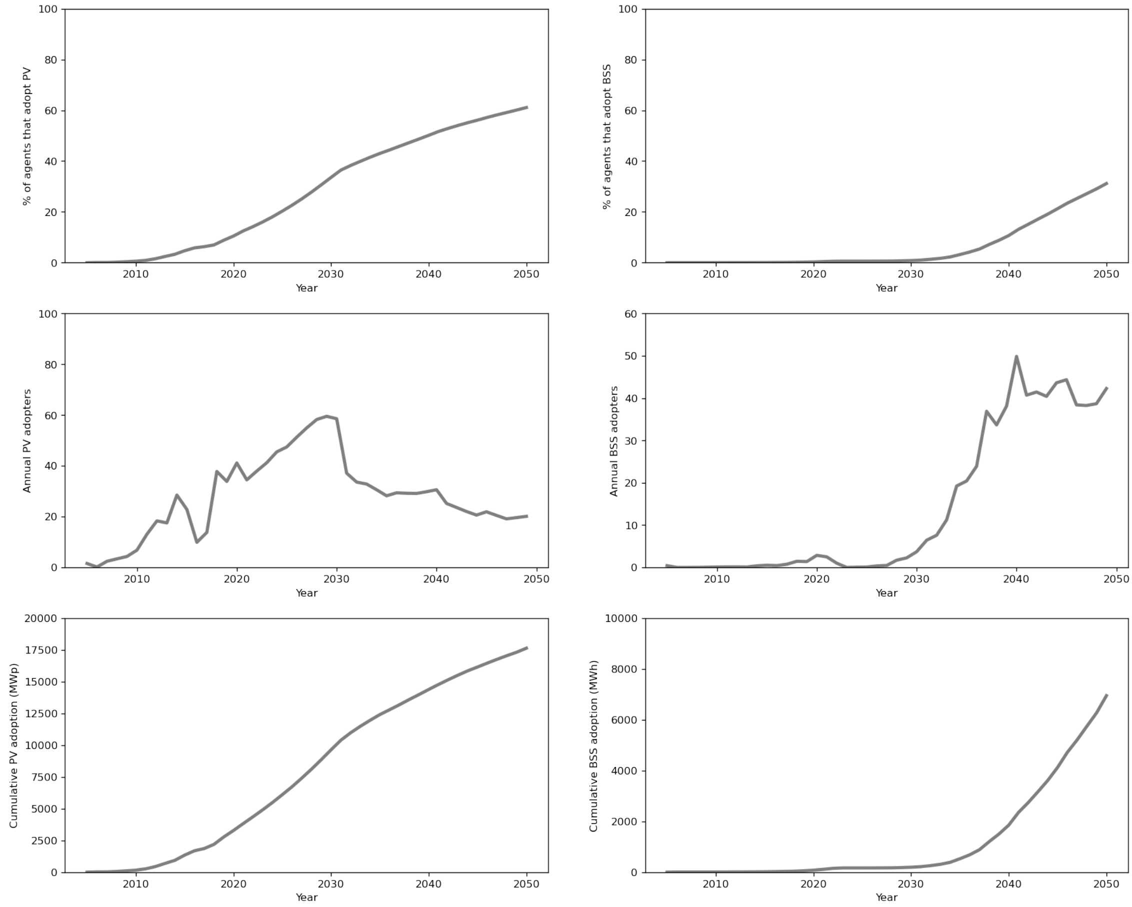


Figure 7.1: Diffusion of PV and BSS (BAU)

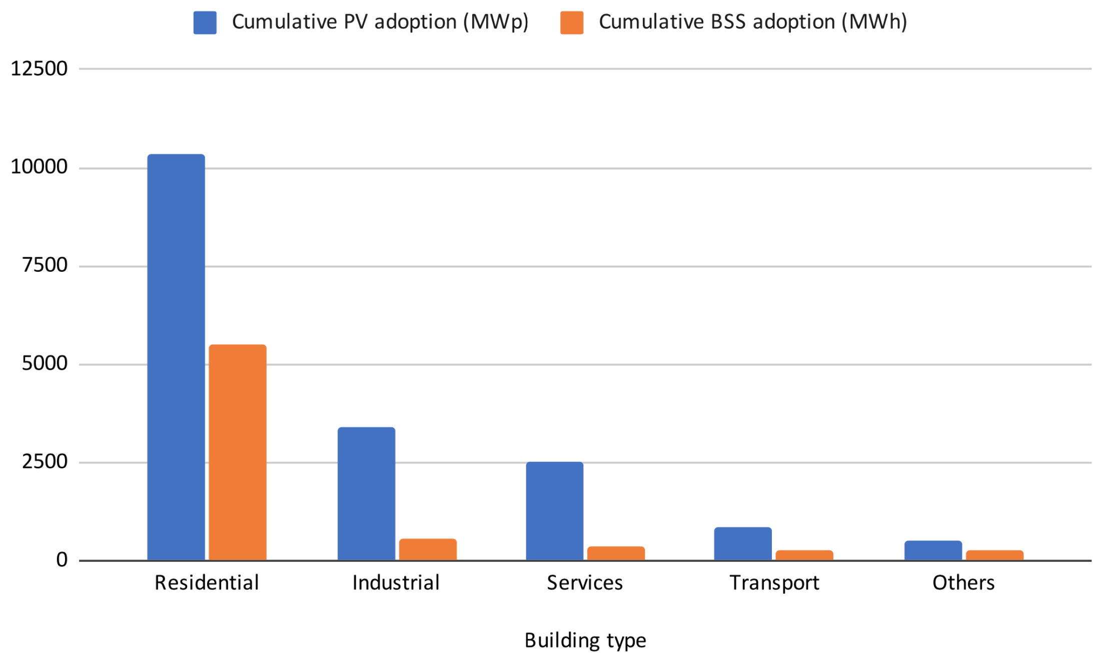


Figure 7.2: PV and BSS adoption per building type

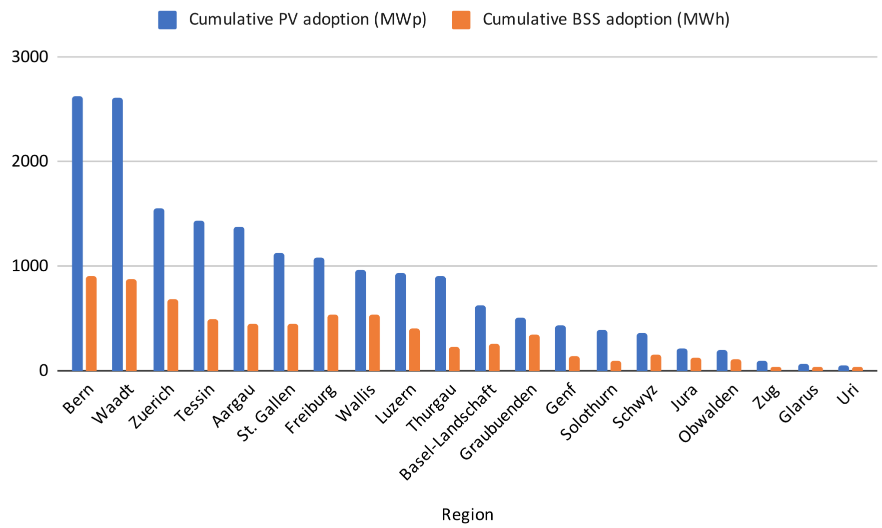
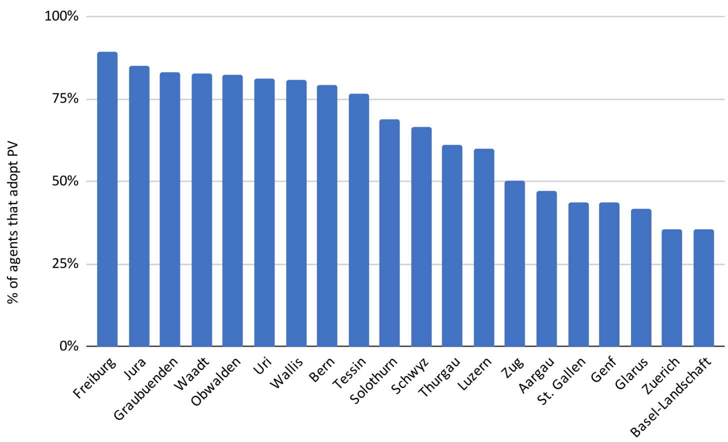
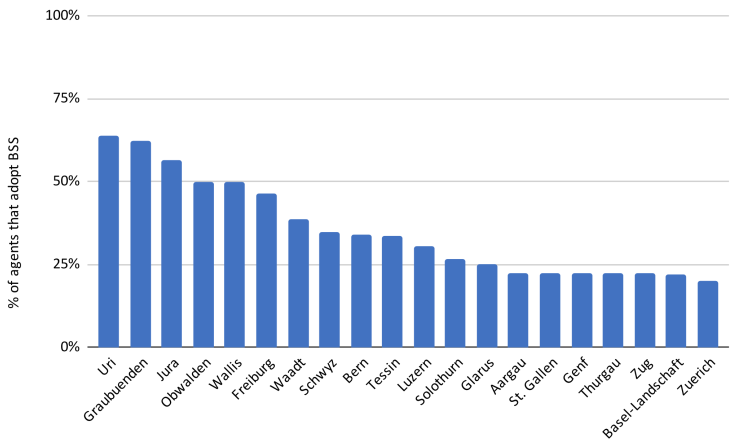


Figure 7.3: Cumulative capacity of PV and BSS adoption by 2050 per region



(a) Solar PV



(b) BSS

Figure 7.4: Percentage of agents adopting the technology per region

7.2 Policy Scenarios Results

To measure the effect of policies on diffusion, the model is run for the five policy scenarios and twenty-eight individual scenarios.

7.2.1 PV Adoption

Fig. 7.5 shows the effect of the five policy scenarios on the diffusion of PV. Weak policy results in a 40% drop in the number of adopters compared to BAU. The lack of subsidies that incentivize PV like FIT and one-time remuneration affect the profitability of solar PV and discourages the adoption by agents. The PV adoption in the case of Strong policy: PV friendly increases the adoption by 30%. The continuation of one-time remuneration for PV and increasing the FIT rate by 50% helps to avoid the drop in the adoption rate after 2031 that occurs in BAU case. This policy helps to maintain the adoption rate after 2031, and further facilitates PV diffusion. Strong policy: BSS friendly does not affect PV adoption as PV is independent of BSS and can be installed as a stand-alone PV system. Strongest policy does not cause a further increase compared to Strong policy: PV friendly as the addition of subsidies incentivizing BSS does not affect PV.

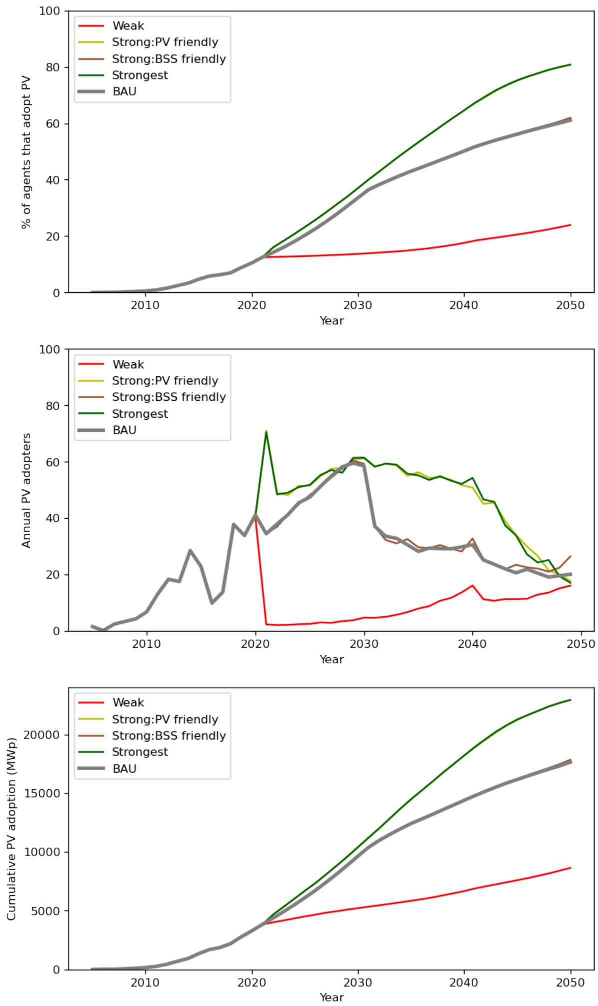


Figure 7.5: Diffusion of PV with different policy scenarios

7.2.2 BSS Adoption

Fig. 7.6 summarizes the adoption of BSS in the case of five policy scenarios. Weak policy increases the BSS adopters initially, but later the number of adopters drop compared to BAU. As initially there are no subsidies that incentivize PV like FIT, so the agents do not receive remuneration for the excess PV electricity. Therefore, it is more attractive for the agent to increase its self-consumption by installing a BSS. But in later years, as PV adoption further decreases due to lack of incentives, and as battery adoption is dependent upon PV adoption, the BSS adoption decreases. The BSS adoption rate in the case of Strong policy: PV friendly decreases as an increase in PV subsidies makes adopting a BSS less attractive than a standalone PV system. Although in this case, the cumulative BSS adopters by 2050 remain the same as BAU as the battery becomes cheaper in later years.

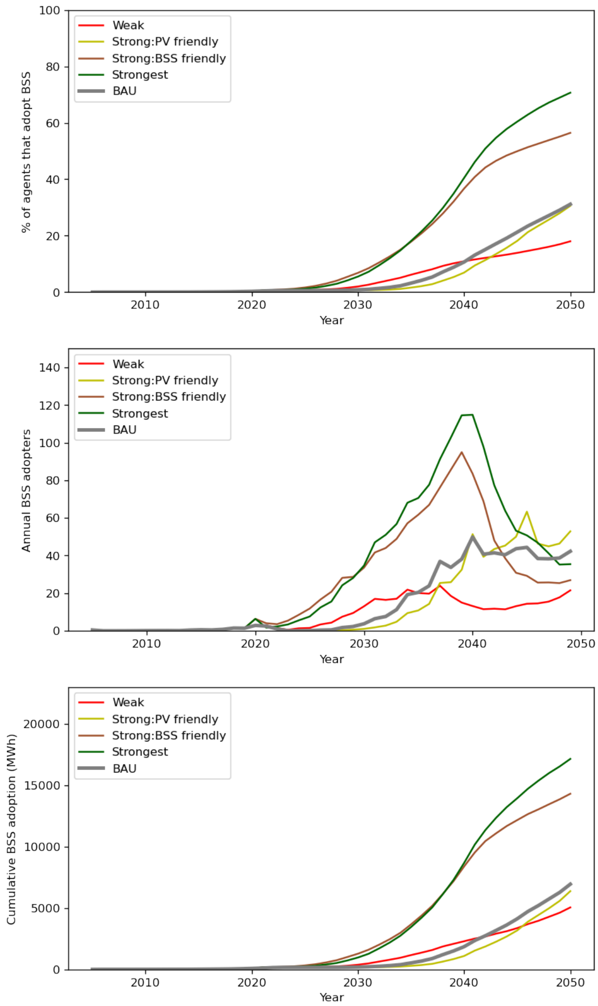


Figure 7.6: Diffusion of BSS with different policy scenarios

Strong policy: BSS friendly greatly increases the number of adopters and the adoption rate. An aggressive information campaign results in more agents developing a positive intention for adopting BSS, and subsidies for battery further incentivize its diffusion. Strongest Policy has the most effect on BSS diffusion. The increase in adoption, in this case, is greater than the Strong policy: BSS friendly signifying the strong dependence of BSS on solar PV. As in the model, BSS cannot be installed as a standalone system and has to be installed with PV, the policies incentivizing both PV and BSS results in the greatest increase in the adoption.

7.2.3 Regional Results

At the regional level adoption for PV (See Fig. 7.7), the Weak policy decreases the adoption in every region by a substantial percentage signifying the importance of subsidies for a uniform adoption of PV in Switzerland. Continuing one-time remuneration and increasing FIT rate help the regions with low adoption realize their full potential. For example, Zuerich has low adoption due to its low FIT rate, but the Strongest and Strong: PV friendly policy increases the cumulative adoption by 110%. More than 70% increase in cumulative adoption happens in the region of St. Gallen and Glarus that had a very low percentage of adopters in BAU case due to low solar irradiation. These policies help to compensate for the low FIT rates and smaller savings due to low solar irradiation in these regions and encourage adoption. The percentage of PV adopters increases almost by 100% in Zuerich, St. Gallen, and Aargau.

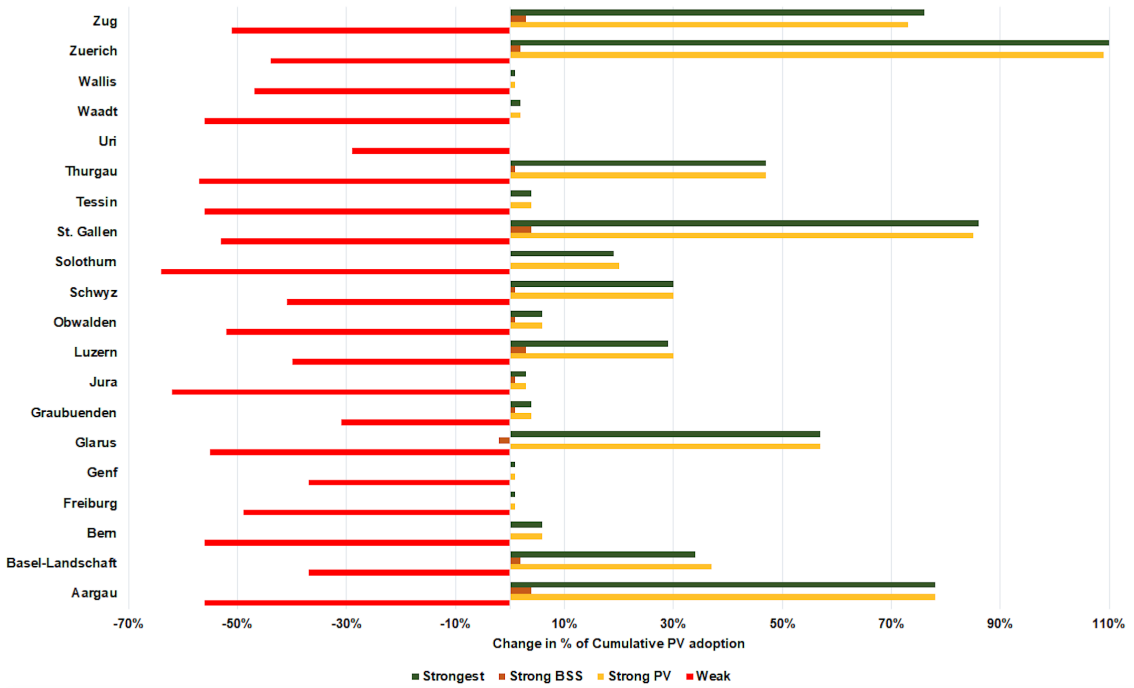


Figure 7.7: Percentage change in cumulative adoption of PV with different policy scenarios per region

For BSS regional adoption (See Fig. 7.8), the Weak policy decreases the battery adoption in all regions except Thurgau. The small increase in BSS adoption in Thurgau might be because of its high FIT rate in the BAU case. Since Thurgau receives adequate solar irradiation, the absence of FIT subsidy encourages more battery adoption to store the excess PV electricity generation. Strong: PV friendly policy decreases the adoption for every region except Zuerich, Glarus, and St. Gallen. These three regions had the lowest adoption of PV in BAU. As BSS installation heavily relies on PV adoption, low adoption of PV limits the adoption of BSS in these regions. PV friendly policies increase PV adoption and therefore, increases the BSS adoption in Zuerich, Glarus, and St. Gallen.

Strong: BSS-friendly policy greatly increases its adoption in all regions, the highest being about 230 % in Thurgau. As the BSS adoption highly depends upon PV, combining the instruments of both the policies (Strong: PV friendly and Strong: BSS friendly) in the Strongest policy escalates the BSS adoption for all regions. The highest increase in cumulative adoption being about 370% in Aargau, and about 300 % in Thurgau.

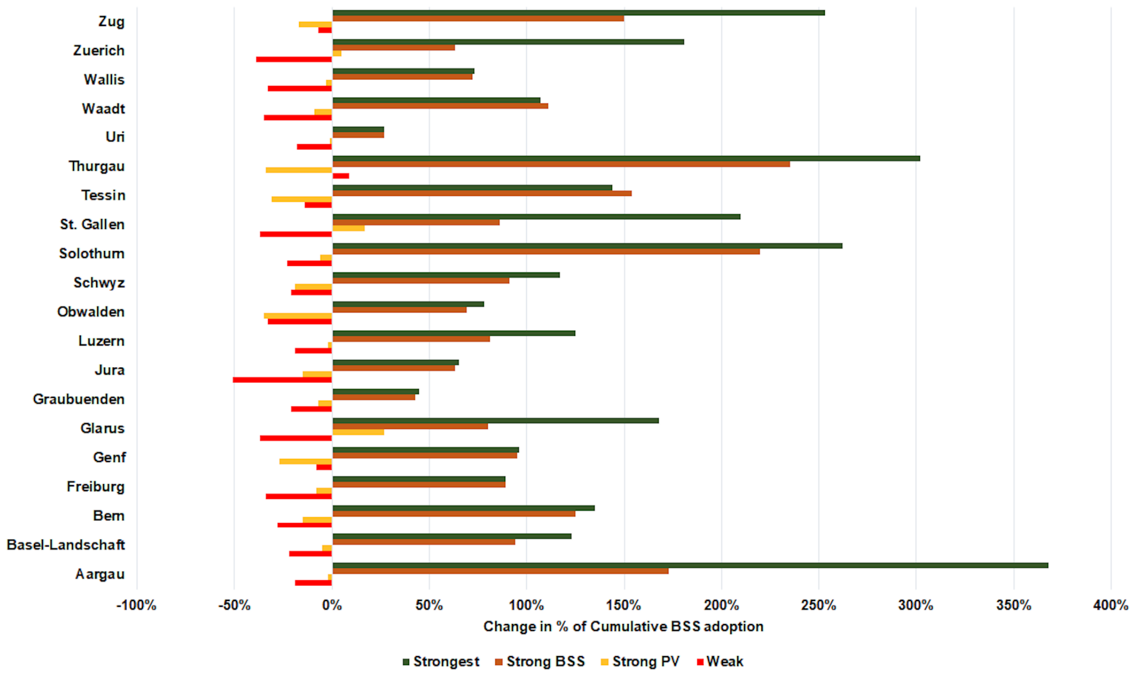


Figure 7.8: Percentage change in cumulative adoption of BSS with different policy scenarios per region

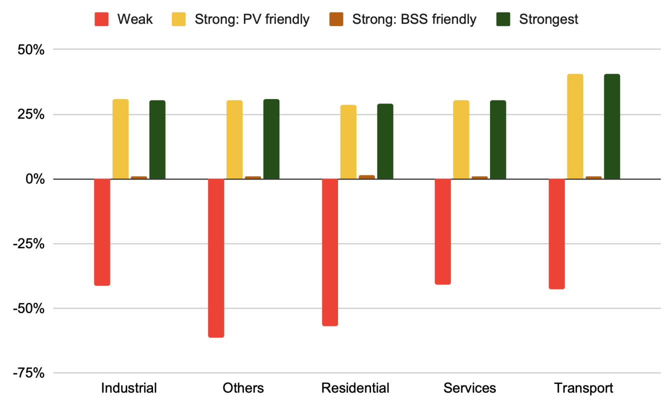
Table 7.1 summarizes the percentage change in total electricity generated from 2021 to 2050 for each policy scenario, the percentage change in the total electricity self-consumed, and the percentage change in the total electricity fed into the grid compared to the BAU. An increase in PV adoption increases total electricity generated, and faster BSS adoption increases self-consumption of the agent.

Table 7.1: Percentage change compared to BAU for each Policy Scenario (2021 - 2050)

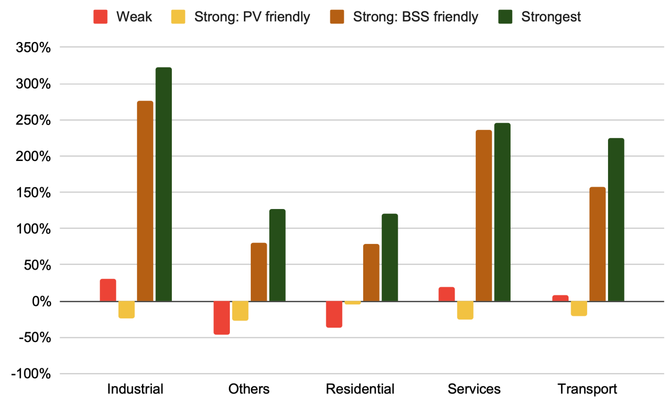
Scenario	Electricity Generated	Electricity Self-Consumed	Electricity Fed to Grid
Weak Policy	- 48%	- 41%	- 54 %
Strong: PV friendly	+ 22%	+ 27%	+ 17%
Strong: BSS friendly	+ 0%	+ 22%	- 18%
Strongest Policy	+ 22%	+ 46%	+ 2 %

7.2.4 Building Type

Fig. 7.9 shows how the policy scenarios affect the adoption in building types. In the case of PV, the Weak policy results in a drop for all building types and more than a 50 % drop in residential and other building types. Strong: PV friendly policies result in the greatest increase in adoption in transport building type. The Weak policy results in an increase in the BSS adoption for industrial, services, and transport building types. As industrial and service buildings have larger demands and larger PV size installations, having no subsidies like FIT encourage these building types to adopt BSS so that they can store their surplus electricity and use it to cover their demand when PV generation is not enough (as BSS, in this case, becomes more profitable). Stong: PV friendly policies decrease the adoption of BSS for all building types. The Strong: BSS friendly policy and Strongest policy causes an increase in BSS adoption for all building types.



(a) Solar PV



(b) BSS

Figure 7.9: Percentage change in cumulative adoption with different policy scenarios per building type

7.2.5 Summary: Cumulative Adoption by 2050

Table 7.2 summarizes the range of adoption of PV and BSS in different scenarios. In the table, the lower limit is the adoption when the model is run with best-fit curve weights, whereas the upper limit is when the model is run with realistic fit curve weights.

Table 7.2: Cumulative adoption range by 2050

Scenario	Cumulative PV adoption (GWp)	Cumulative BSS adoption (GWh)
BAU	11.8 - 17.6	5.7 - 6.9
Weak Policy	7.7 - 8.6	4.6 - 5
Strong: PV friendly	12.4 - 22.9	5.2 - 6.4
Strong: BSS friendly	11.9 - 17.8	9.8 - 14.3
Strongest Policy	13.4 - 22.9	10.6 - 17.2

7.3 Overview

After examining how combined policies will affect the future diffusion rates and cumulative adoption of solar PV and BSS, it is pertinent to investigate the extent of influence each policy exerts on the adoption rates. To do that, one policy is varied in the model while keeping all the other policies to be the same. Fig.7.10 and Fig.7.11 summarizes the effect of the individual policies and combined policy scenarios on cumulative adoption by 2050. The figure shows how the combined policies in policy scenarios have a compounded effect on technology adoption in comparison to the effect of individual policies on adoption. It signifies how the combination of different policy instruments can help achieve the desired adoption rate and meet targets.

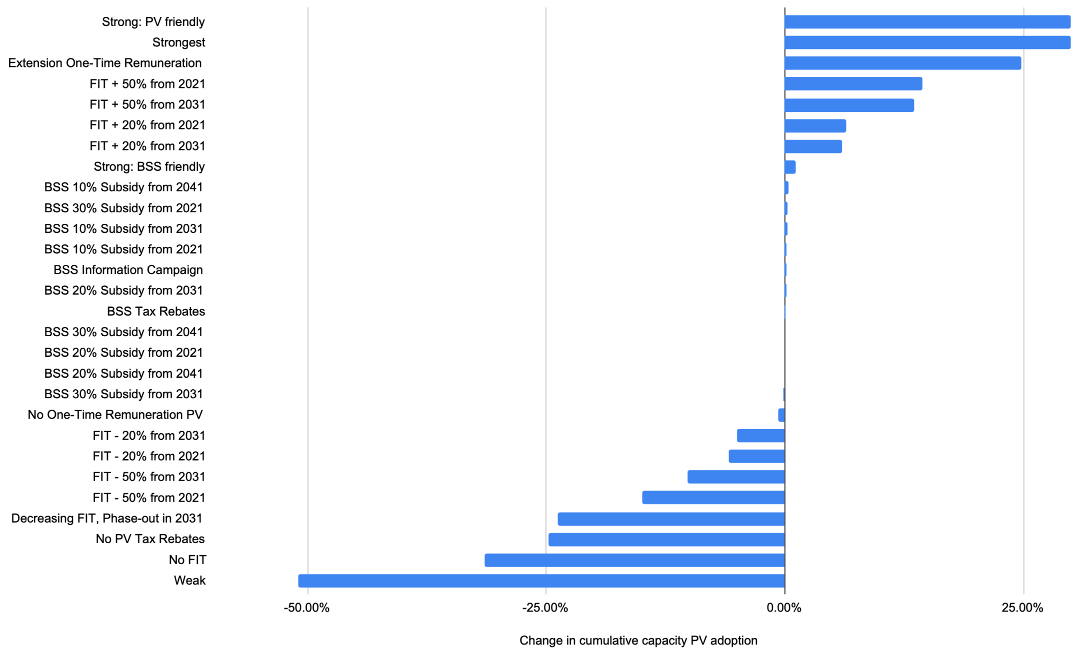


Figure 7.10: Percentage change in cumulative adoption of PV with different scenarios

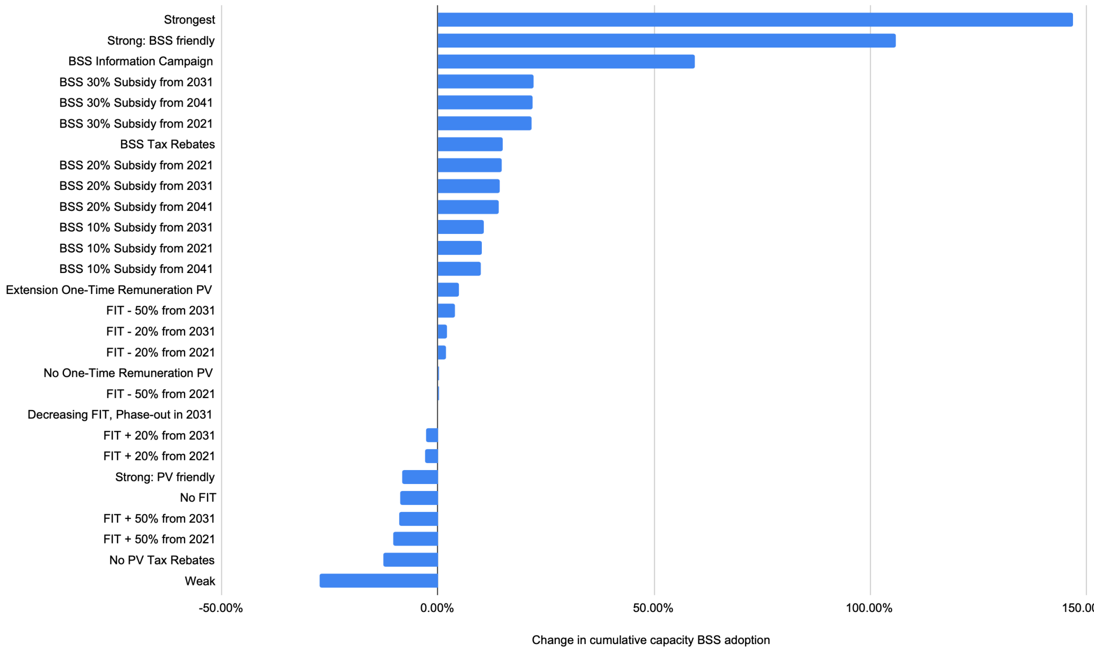


Figure 7.11: Percentage change in cumulative adoption of BSS with different scenarios

7.4 Individual Policy Results: In-depth Analysis

Fig. 7.12 shows the effect of removal and extension of subsidies on adoption. No one-time remuneration for PV drops the PV adoption rate from 2021, but the adoption rates start to increase post-2031 due to lower PV prices and recovers to get a similar cumulative adoption as the BAU case. The removal of FIT and tax rebates drops both the adoption rate and cumulative adoption of PV. Withdrawal of tax rebates decreases the adoption rate of PV, and the drop is even higher with FIT removal. Both cases also observe a second drop in annual PV adopters in 2031 as the withdrawal of tax rebates and FIT accentuate the drop in 2031 (that occurs in BAU due to the ceasing of subsidies). In the case of BSS adoption, the removal of PV one-time remuneration did not affect the BSS. Whereas the withdrawal of PV tax rebates and FIT lowers the adoption of BSS. Removal of FIT slightly increases the battery adoption rate at first, as battery storage increases self-consumption, therefore increases electricity bill savings and compensates for the loss of cash flow due to FIT. But in later years, as the removal of FIT makes the PV adoption lower, so the agents cannot adopt BSS. Extending one-time remuneration for PV till 2050 has a positive effect on solar PV adoption. It helps to maintain the adoption rate after 2031, which otherwise experiences a drop due to the termination of this subsidy. This extension increases the adoption of BSS slightly as well.

As FIT impacts PV adoption, the model tests different FIT policies to assess its full effects. We increase the FIT rate by 20 % and 50 %, and further test if we observe a difference in diffusion if the increase in rate occurs from 2021 or 2031 (See Fig. 7.13). An increase in the rate for FIT increases the cumulative adoption of PV and decreases the cumulative BSS adoption slightly. The time (year) of increase of FIT rate does not affect the cumulative adoption but influences the adoption rates. A jump in annual adoption occurs at the time step when the FIT rate increases. Decreasing FIT (with it ceasing in 2031) results in a high drop in PV adoption and also decreases cumulative BSS adoption.

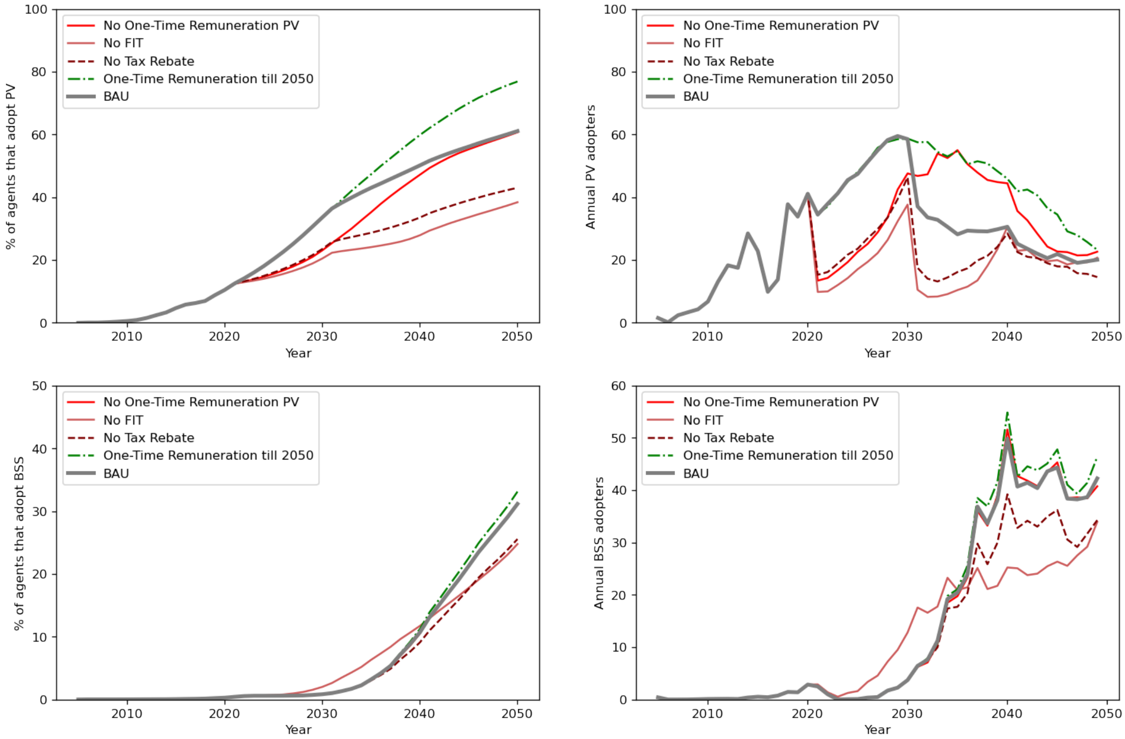


Figure 7.12: Change in PV subsidies

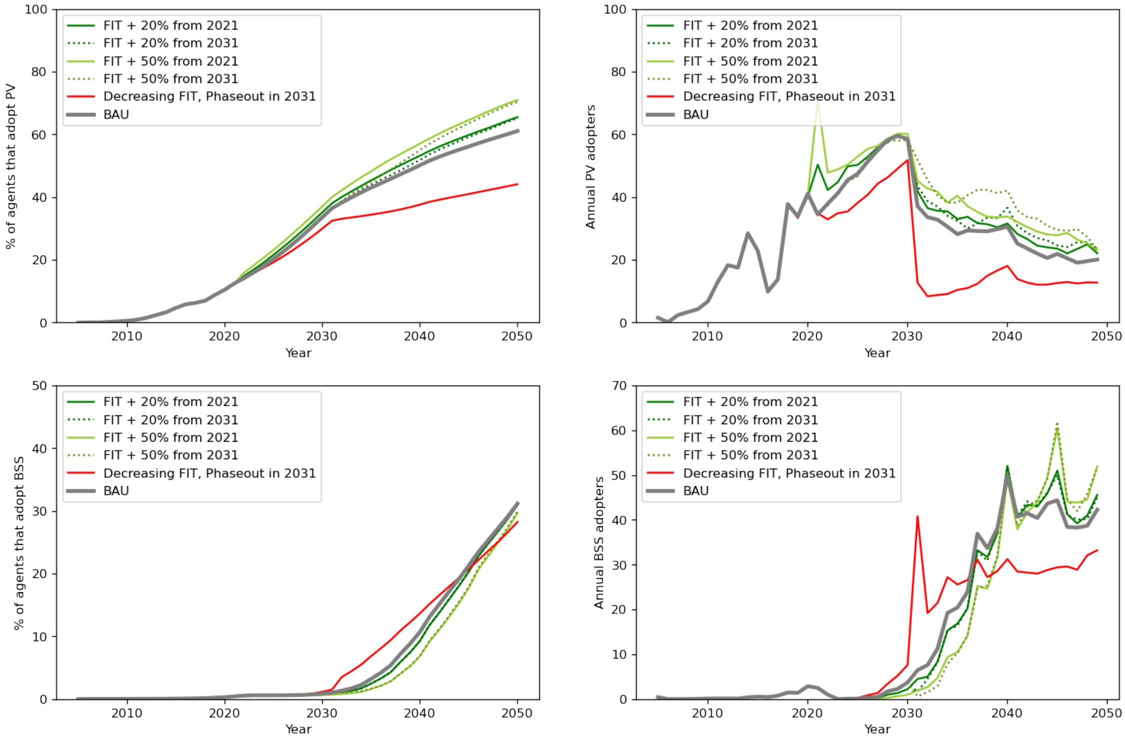


Figure 7.13: Change in FIT rate

But in the case of BSS, initially, after 2030 the adoption increases as the lack of FIT incentivizes BSS. As explained before, BSS increases self-consumption and increases electricity bill savings which compensate for the loss of cash flows due to withdrawal of FIT.

Also, to assess how decreasing FIT affects the adoption, we decrease the FIT rate by 20% and 50%, and further test if we observe a difference in diffusion if the decrease in rate initiates from 2021 or 2031 (See Fig. 7.14). Decreasing the FIT rate decreases the cumulative adoption of PV. Also, It lowers the cumulative adoption of BSS slightly. The time (year) of decrease of FIT rate does not affect the cumulative adoption when there is a 20% decrease in FIT rate. But when the decrease in FIT rate is higher i.e. 50%, the drop in cumulative adoption is higher when the rate decreases in 2021 in comparison to the case when the rate decreases in 2031. In the case of BSS adoption, decreasing FIT decreases the cumulative adoption but the adoption rate increases initially. As explained before, lower FIT incentivizes the BSS. But in later years, as lower FIT discourages PV adoption, the cumulative BSS adoption also falls slightly.

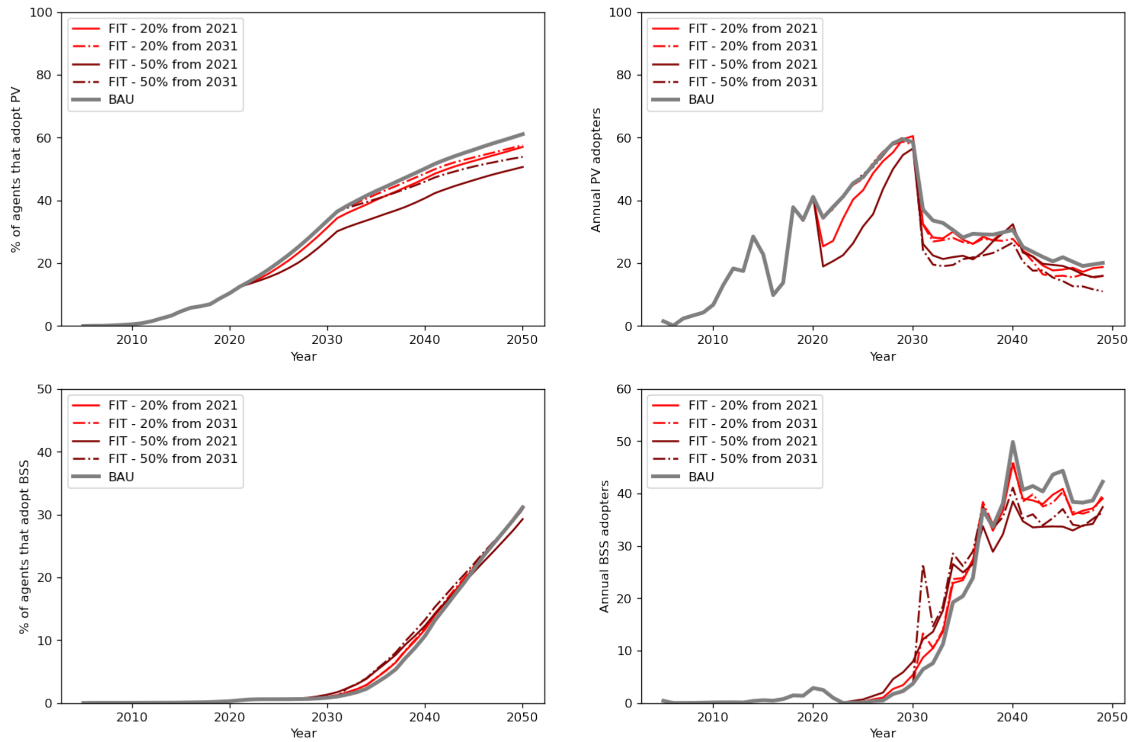


Figure 7.14: Change in FIT rate

The limited number of agents developing positive intention to adopt battery acts as a constraint for maximizing battery adoption. The scenario in Fig. 7.15 looks in to see how an information campaign can help address this and accelerate the BSS diffusion. We assume that an aggressive information campaign increases the available information of the BSS of the agent by 35 % every year from 2021 to 2040 until it reaches a maximum (100%) in 2040. An increase in available information for the agents positively influences the intention. Thus, it increases the number of agents considering BSS adoption and further increases BSS cumulative adoption and adoption rates. The annual adoption reaches a maximum in 2040, beyond which the adoption rate gets slower. Further, we consider another case where the BSS is eligible for tax rebates similar to PV. The introduction of tax deductions for BSS increases the diffusion rate (more battery is adopted earlier), but the cumulative adoption increases only slightly to the BAU (as low intention limits the adoption). Both of the policies are BSS specific, so do not affect PV adoption.

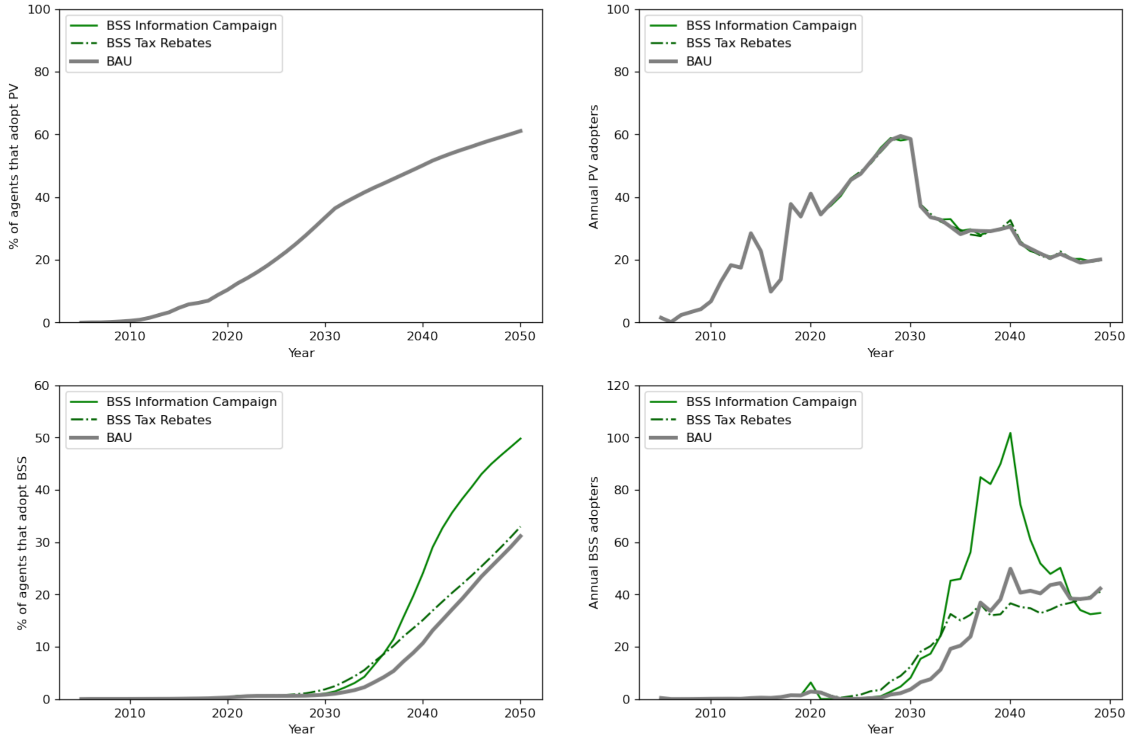
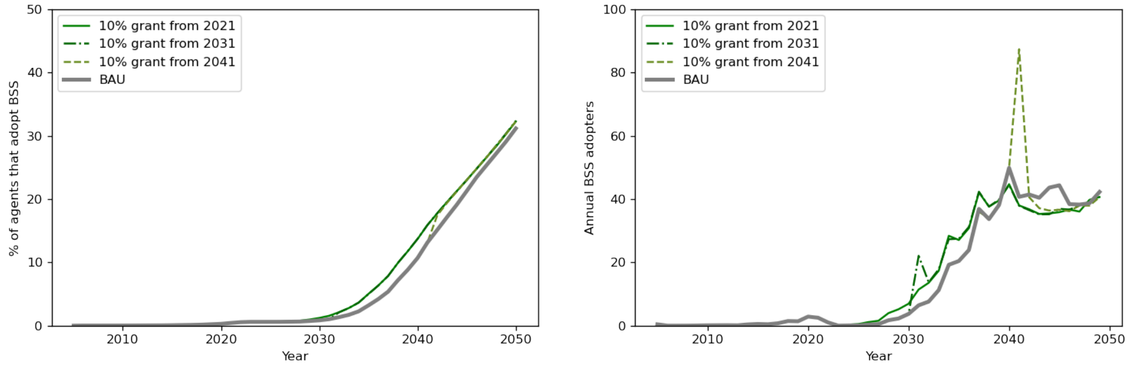
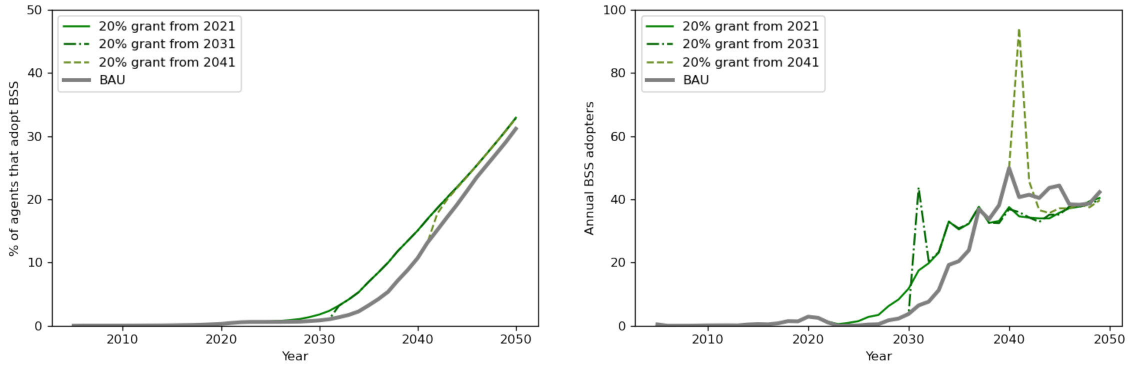


Figure 7.15: Information campaigns and tax rebates for BSS

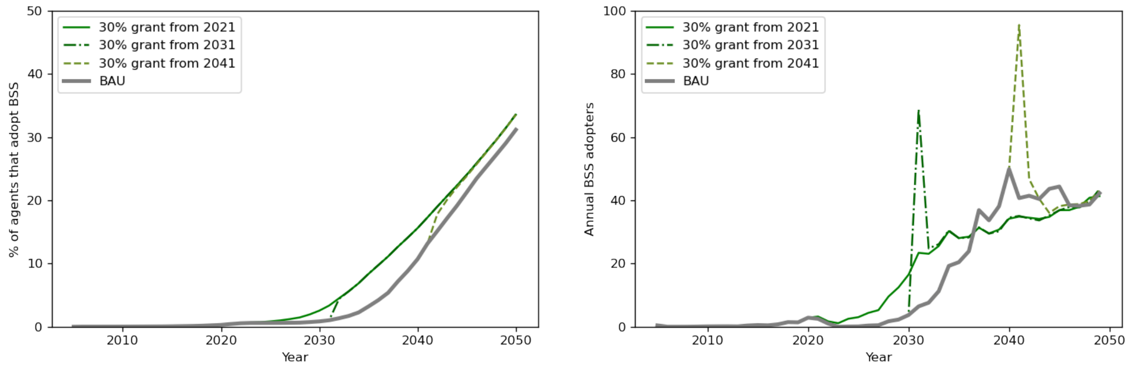
As batteries are expensive, introducing a policy providing subsidies on battery investment costs can influence the adoption rates of BSS. Fig. 7.16 shows how different subsidy rates for BSS and the time of introduction of the subsidy influence the diffusion. In this policy, the BSS is eligible for a one-time battery subsidy of 10 %, 20%, and 30% of the investment costs. Further, to examine the effect of timing, this policy with each subsidy rate commences from 2021, 2031, and 2041 respectively. The increase in the battery subsidy increases the diffusion rate of BSS. The cumulative battery adoption only experiences a slight increase, but this increase rises with a higher subsidy rate. The cumulative adoption does not experience a large increase as a lower number of agents develop the intention to adopt BSS. Thus, it acts as an upper constraint in maximizing adoption despite high battery subsidies. Also, the introduction of the subsidy in 2031 or 2041 results in a high jump in the number of adopters in the following year. But then it drops to follow the adoption curve of the case when the subsidy starts in 2021. It shows that most of the agents having a positive intention for battery adopt the technology the moment the subsidy is introduced (as the battery investment becomes profitable). Battery subsidies do not affect the adoption of PV, and their adoption curves remain the same as BAU.



(a) BSS subsidy 10%



(b) BSS subsidy 20%



(c) BSS subsidy 30%

Figure 7.16: Effect of BSS subsidy on adoption

Chapter 8

Sensitivity Analyses

8.1 Overview

We vary various parameters in the model to see how it affects the results of the model. Fig. 8.1 and Fig. 8.2 summarizes the changes observed for PV and BSS respectively. For PV, changing the IRR threshold to 5%, decreasing PV prices by 50 %, and lowering the sizing factor to 0.5 has the largest positive impact on the cumulative number of PV adopters by 2050. Whereas increasing the IRR to 20 % and increasing the PV prices by 50% has the largest negative impact on the cumulative number of PV adopters by 2050. Regarding BSS adoption, decreasing the peer effect radius to 5 km, decreasing the IRR to 5%, and decreasing BSS prices by 50% has the most positive impact. Increasing the IRR threshold to 20 %, 15 %, and an increase in BSS price by 50 % results in the most negative impact on the number of BSS adopters.

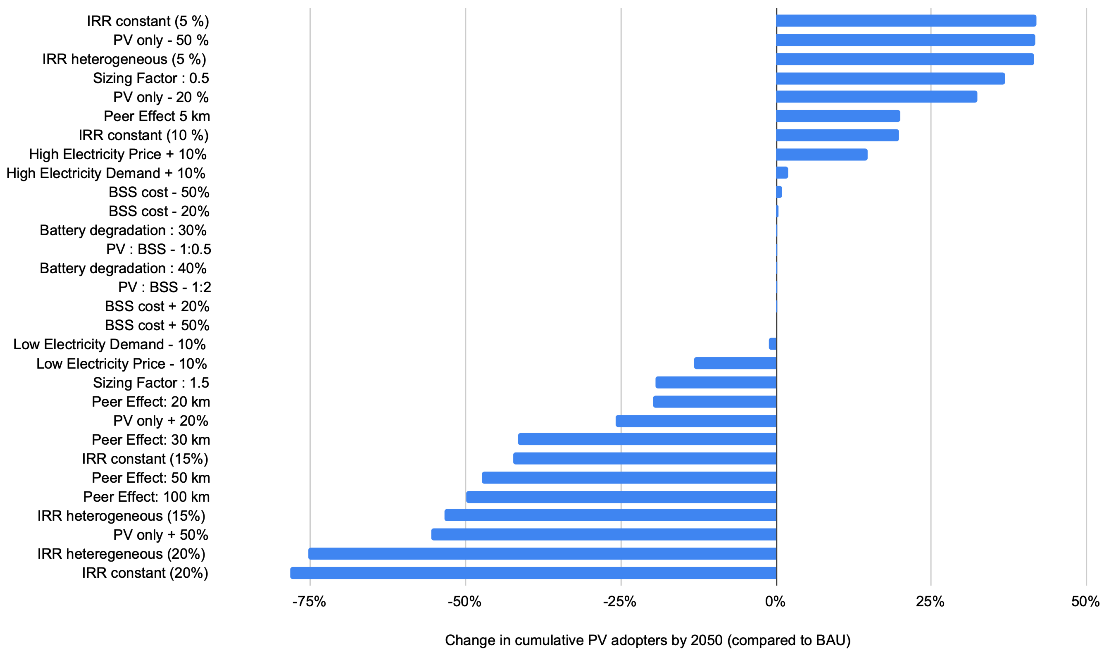


Figure 8.1: Percentage change in cumulative PV adopters by 2050

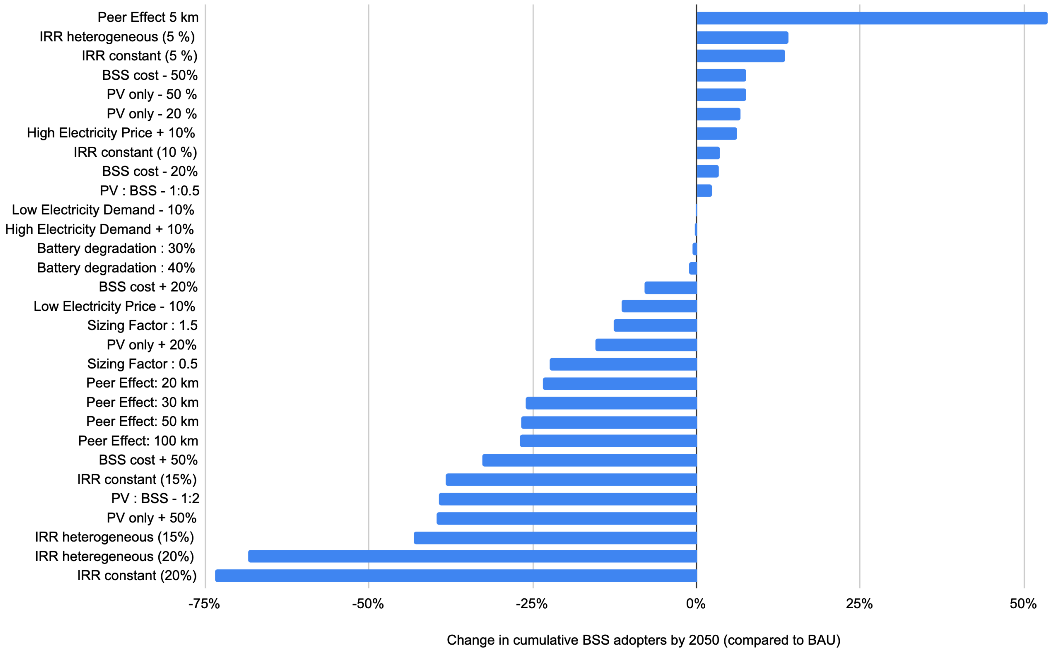


Figure 8.2: Percentage change in cumulative BSS adopters by 2050

The following sections in this chapter discuss the sensitivity analyses in-depth to see how changing different parameters influence the adoption from 2021 to 2050. We perform the sensitivity analysis for two classifications i.e. Techno-economic Inputs and Modelling Assumptions.

8.2 Techno-economic Inputs

Solar PV Prices: An increase in the PV prices by 20% and 50% reduces the PV and BSS adopters (see Fig. 8.3). An increase in PV prices also decreases the BSS adoption as BSS is installed in conjunction with the PV to store excess PV electricity generation. Therefore, the installation of BSS depends upon the installation of PV systems. Similarly, a decrease in the prices of PV by 20% and 50% increases the adoption of both PV and BSS. The increase in BSS adoption is not very high, as the number of agents developing the intention to adopt BSS acts as a limiting factor.

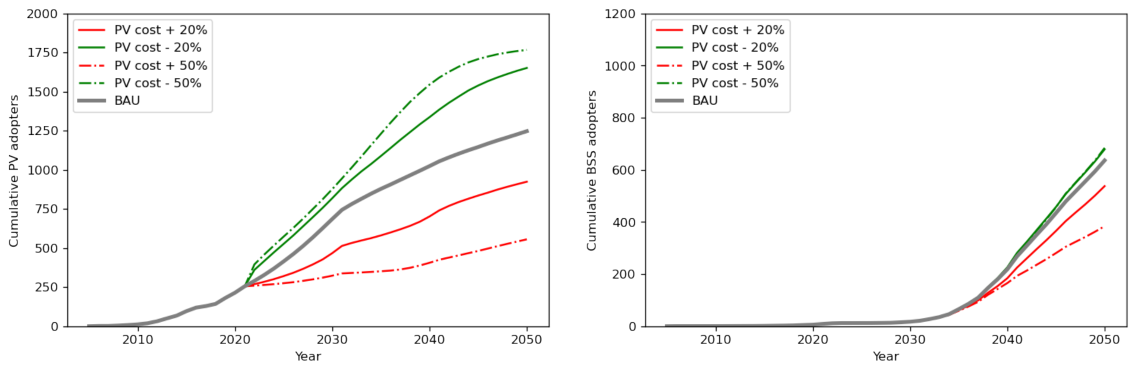


Figure 8.3: Effect of change in PV prices

Battery Prices: An increase in the BSS prices by 20% and 50% reduces the BSS adopters (see Fig. 8.4). A change in BSS prices does not affect PV adoption as adopting a PV system is independent of the BSS installation. Similarly, a decrease in the prices of BSS by 20% and 50% (maybe through a new radical innovation) increases the adoption of BSS. The increase in cumulative BSS adoption is not very high due to a limited number of agents having a positive intention to adopt BSS. But a decrease in the BSS prices greatly accelerates the battery adoption rate as the technology becomes profitable earlier, i.e. before 2030 as opposed to after 2030 in the BAU case.

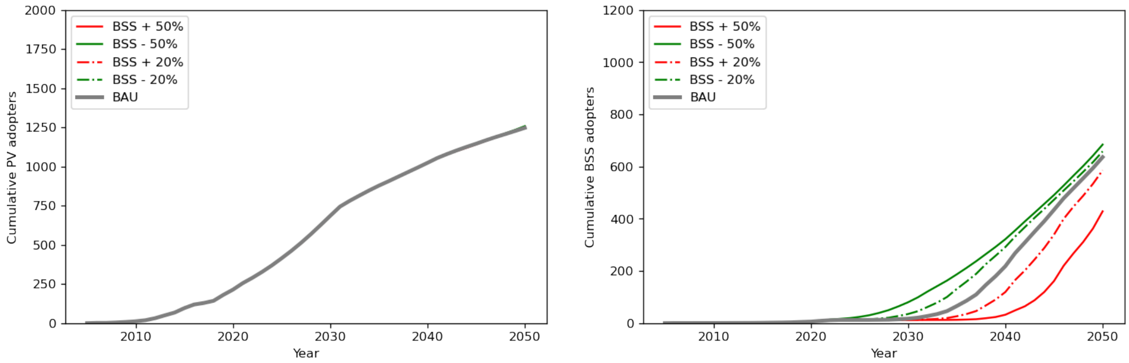


Figure 8.4: Effect of change in BSS prices

Electricity Prices: The effect of a 10% increase/decrease in the electricity prices every year (e.g. if the retail electricity price for an agent is 20 Rp./ kWh in 2025, an increase of 10% would result in the price to be 22 Rp./ kWh in 2025) increases/decreases the adoption of both PV and BSS (Fig. 8.5). The increase in the electricity bill savings due to higher electricity prices makes the investment more profitable. Decreasing electricity prices decreases the PV and BSS adoption as lower electricity prices lead to lower electricity bill savings making the technology less economical.

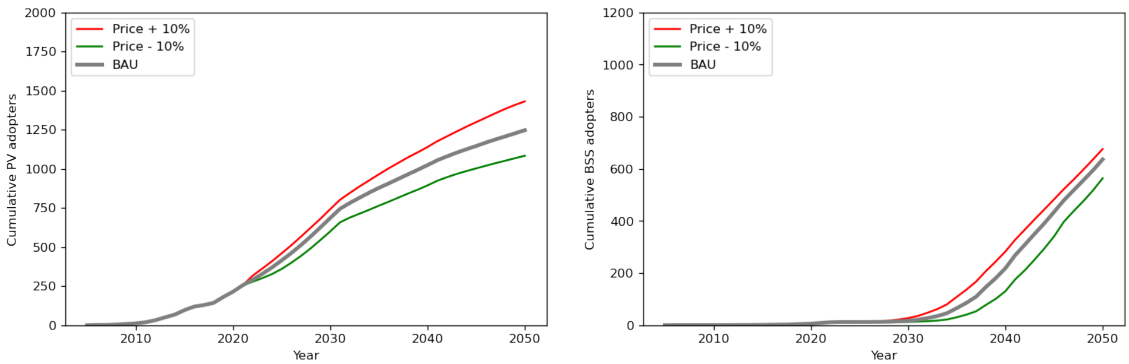


Figure 8.5: Effect of change in electricity prices

Battery Degradation: Battery degradation rate is increased from 20 % (BAU) to 30% and 40% to assess how will it affect the results (see Fig. 8.6). Increasing battery degradation rate does not affect the PV adoption but results in a slight decrease in the battery adoption rate. The increase in battery degradation only slows the adoption rate of batteries slightly and does not have a noticeable effect on the cumulative battery adoption observed at the end of the simulation.

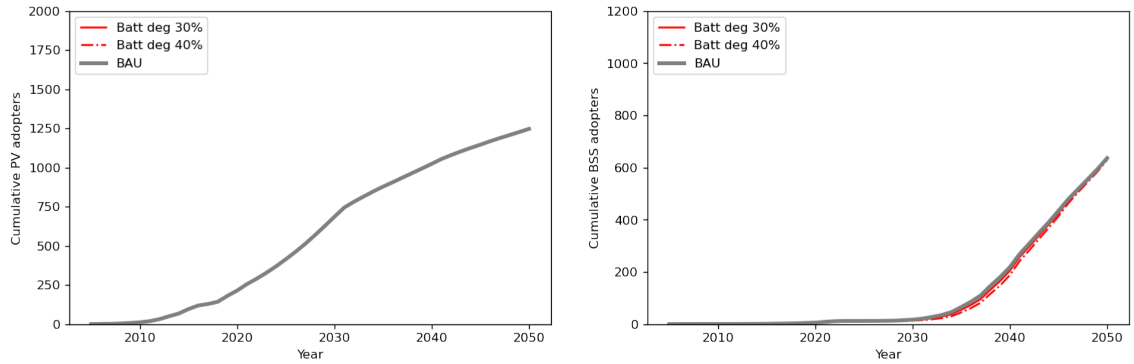


Figure 8.6: Effect of change in BSS degradation rate

Electricity Demand: For examining the effect of electricity demand, the demand for each agent is increased and decreased by 10% from the BAU case every year (e.g. if the electricity demand of an agent for 2025 is 3000 kWh, an increase of 10% would result in the demand to be 3300 kWh for 2025). The variations of electricity demand result in no change in the cumulative number of adopters for both PV and BSS (See Fig. 8.7). As the sizing factor depends upon the agents' electricity demand, a change in demand only impacts the PV size installed by the agent. The profitability calculation for the agent remains unchanged. But with an increase and decrease in electricity demand, there is an increase and decrease in PV size installations respectively. Therefore, the cumulative capacity of PV and BSS installed increases/decreases with the increase/decrease of electricity demand.

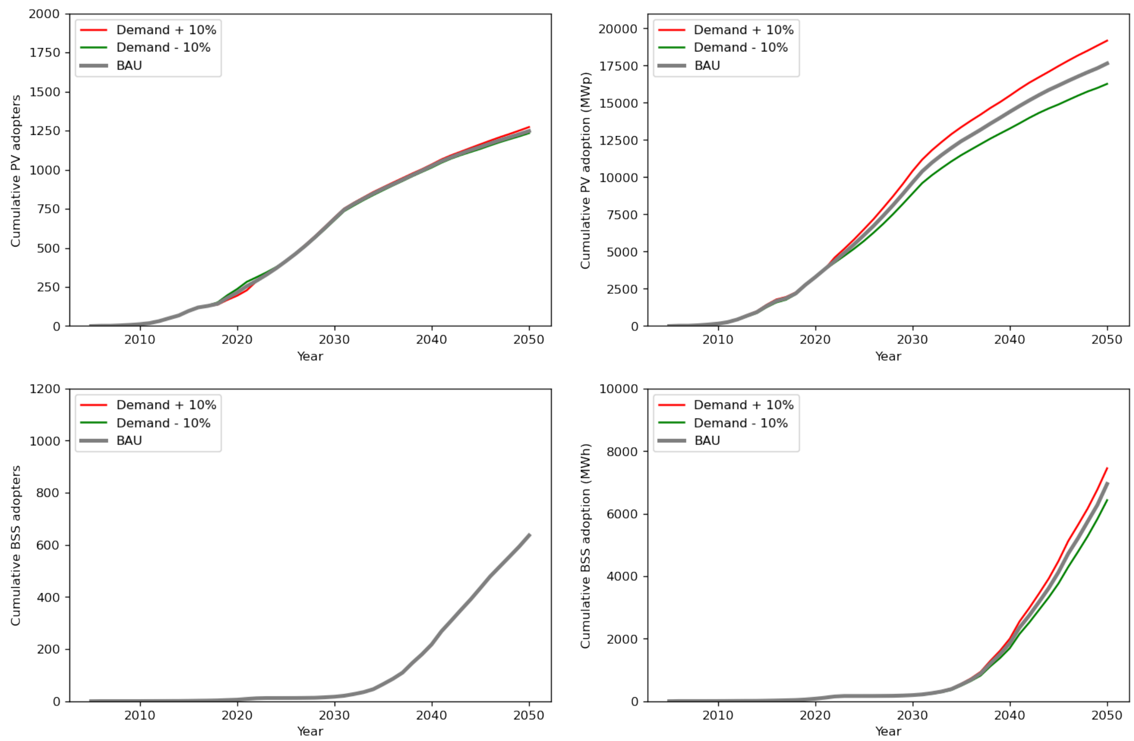
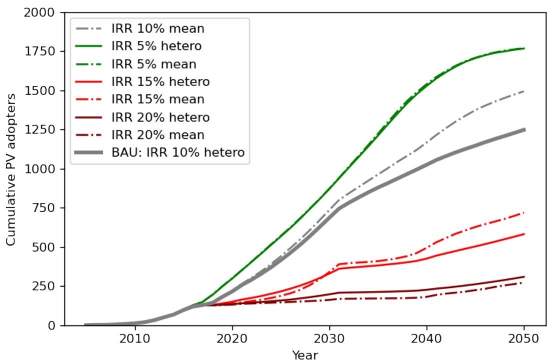


Figure 8.7: Effect of change in electricity demand

8.3 Modelling Assumptions

IRR: The model assumes the personal discount rate (IRR threshold) to be heterogeneous and allots it to each agent based on a truncated normal distribution having a mean of 10% (standard deviation is 20% of the mean). We examine the model to see its sensitivity to the IRR threshold by varying the mean to 5%, 15%, and 20% and further testing them for both instances where IRR is constant and heterogeneous. Increasing the threshold decreases the adoption as shown in Fig 8.8. Heterogeneity of threshold increases the adoption compared to when IRR is constant for all agents when the IRR threshold function mean is 20%. In the case of heterogeneous IRR threshold with a mean of 15 %, initially, the adoption is more (compared to when IRR is constant with 15%) as agents with lower threshold adopt early, but as the agents have a higher threshold in the later years, the adoption decreases. When the IRR threshold function mean is lower than 15% the constant IRR shows more adoption than heterogeneous IRR. When the mean is 5%, the heterogeneity does not affect the adoption because of the small standard deviation and narrow range of IRR, therefore both constant and heterogeneous threshold shows same adoption curve. When the IRR decreases and is very low (when agents are willing to adopt the technology despite low returns), the whole adoption depends solely on intention, and profitability and incentives no more play a decisive role.



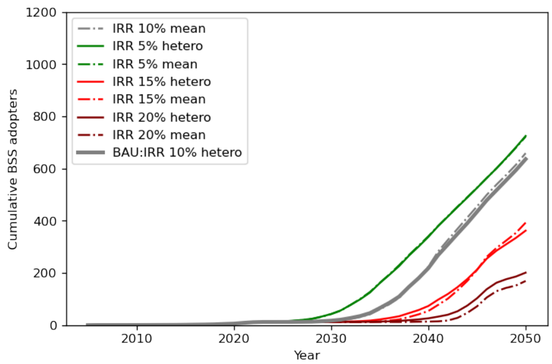


Figure 8.8: Effect of change in IRR threshold

Peer Effects Radius: The radius within which the neighbors' adoption decision influences the peer effects varies from 5 km, 20 km, 30 km, 50 km, and 100 km in Fig. 8.9. An increase in the radius of peer effects decreases the adoption, whereas a decrease in the radius increases the adoption of both PV and BSS. As in a smaller radius, there are fewer neighbors, and an increase in adopters has a higher effect on the agent's intention. As the radius increases, the total number of neighbors also increases, which decreases the value addition in peer effects when one agent adopts the technology. Peer effects drive adoption due to the formation of clusters. A cluster is a group of agents having very high adoption and high peer effects, that drive the diffusion of both PV and BSS. The decrease in the adoption with increasing radius decreases after 50 km and converges beyond it. As a radius beyond this point covers most of Switzerland and represents the nation as a cluster.

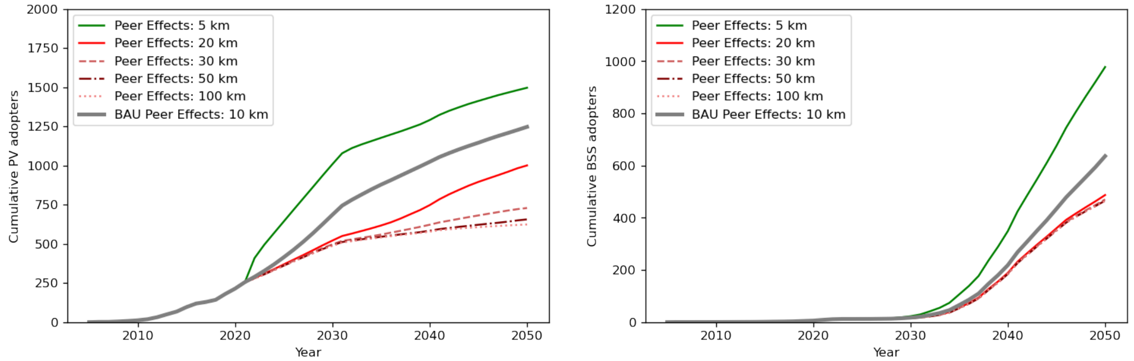


Figure 8.9: Effect of change in peer effect radius

PV size to Battery Size Ratio: The PV to BSS ratio is varied to 1:0.5 (e.g. for 10 kWp solar PV, a 5 kWh battery is installed) and to 1:1.5 (e.g. for 10 kWp solar PV, a 15 kWh battery is installed) (see Fig. 8.10). A decrease in ratio (1:0.5) results in a slight increase in the BSS adoption rate. The cumulative BSS adopters remain the same due to the number of agents developing the intention to adopt BSS acts as a limiting factor. The cumulative capacity of BSS installed decreases in this case due to the smaller size of BSS installed. Whereas an increase in the ratio (1:1.5) decreases the battery adoption as large batteries increase the investment costs, and there is no substantial increase in the PV electricity stored (as PV electricity generation remains the same) which makes the investment less profitable on average. An increase in ratio also results in a decrease in cumulative capacity of BSS adoption due to a way lesser number of agents adopting BSS despite larger battery sizes.

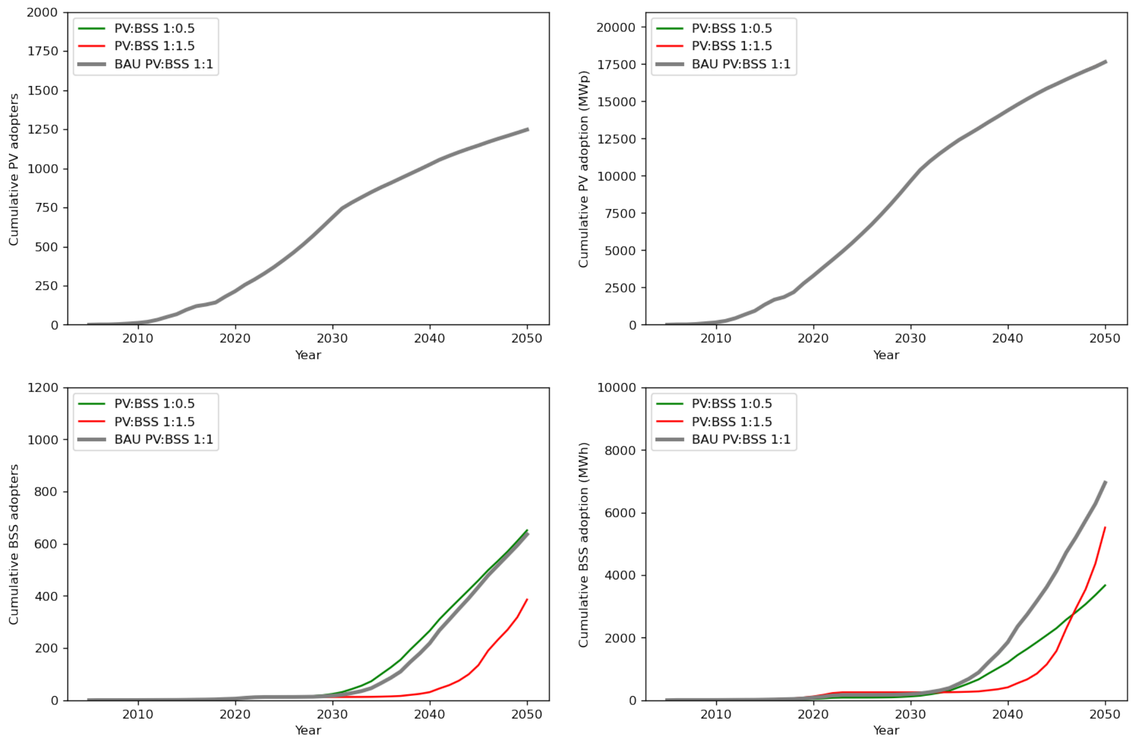


Figure 8.10: Effect of change in sizing ratio of PV and BSS

Sizing Factor: The agent uses a sizing factor to choose the solar PV size to install. The agent installs the PV size such that the maximum ratio of the agent's annual PV generation and its annual electricity demand is one. To see its effect on diffusion, the sizing factor's ratio is decreased and increased to 0.5 and 1 respectively. (see Fig.8.11). A decrease in the sizing factor increases adoption as smaller PV sizes decrease the initial investment costs, increases the self-consumption rate, and makes the investment more economical. The number of PV adopters increases, but as the sizes installed are smaller, the cumulative capacity of PV installed decreases. The increase in adoption shows that smaller PV sizes are more optimal for the agents but not realistic as the buildings install much larger PV sizes in reality (see model validation). A decrease in the sizing factor decreases the number of BSS adopters and the cumulative capacity of BSS adoption. Smaller PV sizes have a higher self-consumption rate and produce lesser excess PV generation that could be stored in the battery, making extra electricity bill savings from using stored electricity from battery unsubstantial. Therefore, BSS adoption decreases. An increase in sizing factor increases the investment costs of solar PV. With the increase in PV size, the self-consumption rate decreases, and the DSO's remunerates the excess electricity fed into the grid. This remuneration (FIT) is lower and is not enough to compensate for the additional investment costs. Thus, this makes it less economically attractive and decreases PV adoption. Despite a decrease in the number of adopters, the cumulative capacity of PV adoption increases due to larger sizes of PV installations. Similarly, BSS adoption decreases as large batteries are not economical due to very high investment costs but the cumulative capacity of BSS installed increases due to the installation of larger sizes of BSS.

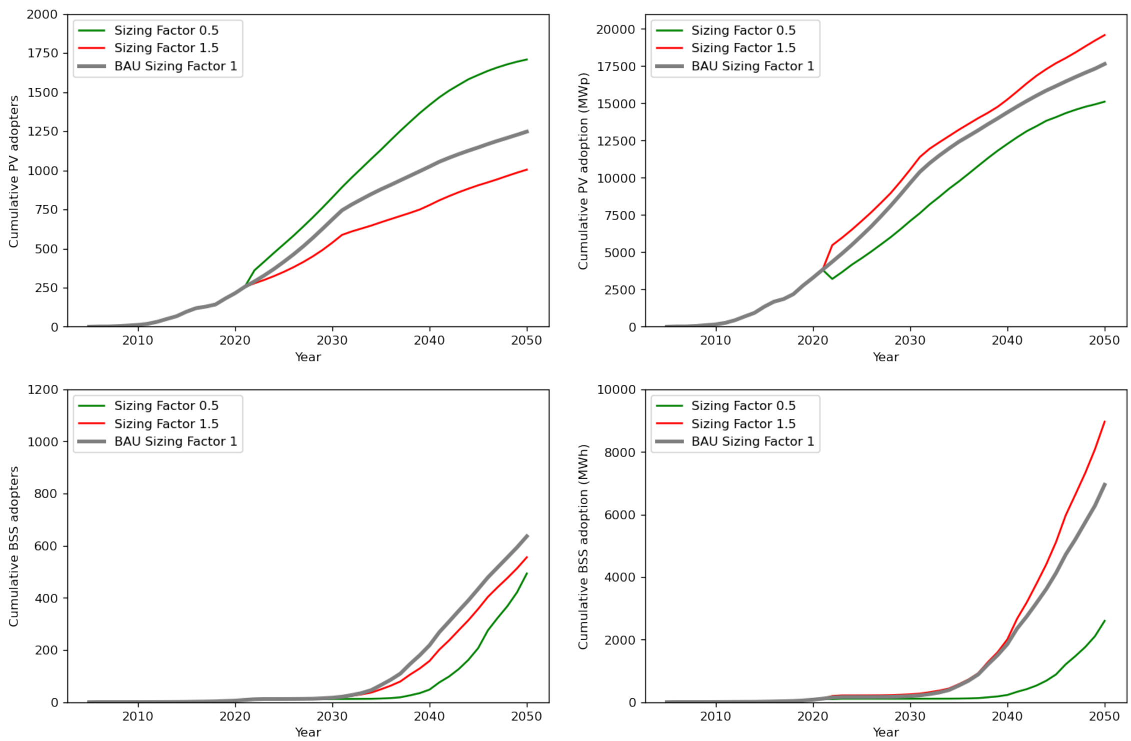


Figure 8.11: Effect of change in sizing factor for PV

Chapter 9

Conclusion

Switzerland is moving towards new energy policies which aim to replace nuclear energy in the electricity mix with non-hydro renewable energy technologies. Out of all the technologies, solar PV has enormous potential, but an increase in renewable energy will lead to uncertainty and volatility in the power system. To make the system safe and reliable, it is pertinent that the power system is flexible. For that, batteries with PV are a promising solution. To this scope, the thesis focuses on examining how the PV and BSS will diffuse in Switzerland and further investigates how policies affect the diffusion curves.

We develop an agent-based model to forecast the diffusion of PV and BSS in Switzerland from 2021 to 2050. In the model, the agent decides to adopt the technology in two steps. First, the model calculates the intention for the agent that indicates whether the agent has the idea to adopt the technology or not. The intention depends primarily on three factors: environmental awareness, peer effects, and available information. All the agents having a positive intention move to the next step, where the agent decides if the investments are profitable or not. Also, highly aware agents having a positive intention and a high awareness leapfrog the economic evaluation step and directly adopt the technology. Further, the agents are classified based on region and building type. We calibrate the model from 2005-2019 using historical adoption data and validate it for 2020. The best-fit weights capture the historical adoption trends well but based on literature and previous research, we calibrate the model further to obtain a realistic fit curve.

With the present policies i.e. the BAU scenario 61% of the agents adopt solar PV by 2050, and 31% of the agents adopt the BSS by 2050. For PV, highly aware agents mainly drive the initial adoption up to 2014. The cumulative PV capacity installed by 2050 is 17.6 GWp which is less than half of Switzerland's total technical solar potential. The BSS becomes profitable in the model only after 2035 (due to the high battery prices initially). The cumulative BSS capacity installed by 2050 is 6.9 GWh. Continuing subsidies like one-time remuneration for PV and increasing the FIT rate help maintain the adoption rate after 2031 and increases the cumulative adoption of PV. An increase in the FIT rate results in a decrease in the adoption rate of BSS as FIT makes PV more profitable and reduces the incentive to adopt BSS. Subsidies on PV do not affect the adoption of BSS as PV is independent and can be installed as a standalone system. Subsidizing battery investment costs are essential to increase BSS adoption, but alone are not enough to drive the installation of BSS to realize its full potential in Switzerland. As battery storage offers a solution to stabilize the potential volatility and uncertainties in the power system due to the increase in renewables, policies specifically focused on increasing the diffusion of battery storage are essential. Non-monetary policies like an aggressive information campaign, with monetary policies offering 30% investment subsidy and provision of tax rebates (similar to PV) for the BSS, can greatly promote its adoption in Switzerland. These policies can increase the cumulative battery adoption by around 110 % when compared to the BAU case. Providing subsidies on battery investment earlier does not greatly impact the cumulative adoption by 2050, but it aids in the faster adoption of battery as the provision of subsidy makes the battery profitable in 2025 instead of 2035. Early battery adoption increases the self-consumption of the agent and makes the agents self-sufficient faster. Combining PV-friendly and BSS-friendly policies does not increase PV adoption but increases the BSS adoption by 40% (from 110% to 150%) as BSS adoption depends on PV installation. Therefore, having policies targeted for both the technologies can help maximize the PV&BSS adoption. Out of all building types, residential buildings have the most solar potential and have the most PV&BSS capacity installed by 2050. On the regional level, in the BAU scenario, Bern has the highest adoption for both PV and BSS, followed by Waadt and Zuerich. Strong policies like the FIT, subsidies for PV and battery, tax rebates drive up adoption in regions like Zurich, Aargau, and St.Gallen (where otherwise low FIT rates, low electricity prices, or low solar irradiation limits the adoption). Therefore, to fulfill the objectives of Energy Strategy 2050 in the considered time frame, subsidies on technology and awareness campaigns are paramount to expedite the diffusion of solar PV and PV&BSS in Switzerland.

The model has certain limitations which point towards the topics that can be addressed in future studies. One limitation of the model is the lack of data on how battery storage systems evolved historically in Switzerland or are expected to evolve in the immediate future years. The availability of more data in this respect in the future would help to calibrate the model concerning battery storage adoption more precisely, thus further fine-tuning the model.

Another limitation of the model is that it assumes that the PV degradation rate during its lifetime is zero. Further, the model assumes that a decrease in cash flow due to battery degradation is constant over the battery lifetime. These assumptions help to decrease the simulation time. Also, to reduce the simulation time further, another limitation is that the model considers 288 hours (24-hour profile for one day of each month, multiplied by 30 to represent the whole year) instead of 8760 hours. Thus, the model does not fully incorporate the daily variations observed in solar PV generation, electricity demand, and electricity prices, and therefore the results may be a little averaged out.

Also, the model assumes that an agent who installs a solar PV will install the technology again after its lifetime is over. In reality, this could be more complex, so to measure this uncertainty around re-installing the technology, the model can include another step based on a new factor called “customer feedback or review”. Surveys and data collecting feedback from present solar PV adopters can quantify this variable. Based on this data, a probability function could decide if the agent chooses to install again immediately or not.

In the model, the Sonnendach database linked with GWR is the primary input to estimate the total technical solar potential of Switzerland. Various studies calculate the technical solar potential of Switzerland using different methodologies. Table A.5 summarizes the comparison of these studies. Varying the total technical solar potential input in the model can assess how it alters the result of technology adoption both at the national and regional level.

Also, the model uses exogenous electricity prices which account for the price increase assuming the capacity of PV installed in the DisTiv optimization model. As electricity prices are a key driver of the diffusion of solar power and battery storage, in the future, the model can be connected to a modeling platform that estimates the development of electricity prices based on technology diffusion in our model. This will allow for feedback loops between the two and helps to make more accurate predictions.

Another enhancement of this model could be to increase the spatial resolution of the ABM below the cantonal level i.e. at the municipality level. Inclusion of different regulations at the municipality level would predict a more realistic diffusion rate, and further, facilitate to model the social factors like peer effects more accurately.

Also, introducing different resizing parameters for different types of buildings will help to model peer effects more effectively. It will more realistically represent electricity demand heterogeneity within a particular building type of region.

A further enhancement of the model could be by introducing more agent classification within each region and each building type based on their socio-economic categories (income or education). Also, conducting detailed surveys in Switzerland will give a better idea about the awareness, perception, and information regarding the technologies like solar PV and BSS, and how they affect the agent's decision-making process. Thus, modeling them based on the collected data will make the model more precise and provide more insights.

Appendix A

Appendix: Tables

Table A.1: Number of agents per region

Region	No. of Agents
Aargau	166
Basel-Landschaft	142
Bern	248
Freiburg	71
Genf	50
Glarus	24
Graubuenden	78
Jura	24
Luzern	78
Obwalden	20
Schwyz	35
Solothurn	71
St.Gallen	151
Tessin	125
Thurgau	93
Uri	10
Waadt	182
Wallis	125
Zug	20
Zuerich	329

Table A.2: Regions and cantons

Region	Cantons
Aargau	Aargau
Basel-Landschaft	Basel-Landschaft, Basel Stadt
Bern	Bern
Freiburg	Freiburg
Genf	Genf
Glarus	Glarus
Graubuenden	Graubuenden
Jura	Jura
Luzern	Luzern
Obwalden	Obwalden, Nidwalden
Schwyz	Schwyz
Solothurn	Solothurn
St.Gallen	St. Gallen, Appenzell Innerrhoden, Appenzell Ausserrhoden
Tessin	Tessin
Thurgau	Thurgau
Uri	Uri
Waadt	Waadt, Neuenburg
Wallis	Wallis
Zug	Zug
Zuerich	Zuerich, Schaffhausen

Table A.3: Buildings classified into types based on GWR code

GWR Code	GWR Classification	Type Assigned
1110	Individual houses	Residential
1121	Buildings with two apartments	Residential
1122	Buildings with three or more apartments	Residential
1130	Residential buildings for communities	Residential
1211	Hotel buildings	Services
1212	Other buildings for short term accommodation	Services
1220	Office buildings	Services
1230	Wholesale and Retail buildings	Services
1241	Stations, Terminal buildings, Telephone exchanges	Transport
1242	Garage buildings	Transport
1251	Industrial buildings	Industrial
1252	Vessels, Silos and Storage buildings	Industrial
1261	Buildings for cultural and recreational purposes	Services
1262	Museums/Libraries	Services
1263	Schools, University buildings, Research Facilities	Services
1264	Hospitals and Health care institutions	Services
1265	Gymnasiums	Services
1271	Agricultural buildings	Others
1272	Churches and other buildings of worship	Services
1273	Monuments, prehistoric sites, statues, buildings for memorials etc	Services
1274	Other buildings like bus stops, wash houses, public toilets	Others

Table A.4: Number of News Articles per year

Year	Solar PV	Battery Storage
2005	118	0
2006	253	0
2007	439	1
2008	511	3
2009	554	9
2010	727	17
2011	1069	21
2012	1088	14
2013	856	22
2014	1066	43
2015	704	91
2016	709	76
2017	-	106
2018	-	171
2019	-	176
2020	-	322

Table A.5: Comparison of various studies estimating technical potential of Switzerland

Study	Technical Solar Potential (TWh)
IEA [62]	15.04
Assouline et al. [63]	17.86
Assouline et al. [64]	16.29
Sonnendach [47]	53.09
Buffat et al. [65]	41.2
Walch et al. [66]	24.58

Appendix B

Appendix: Figures

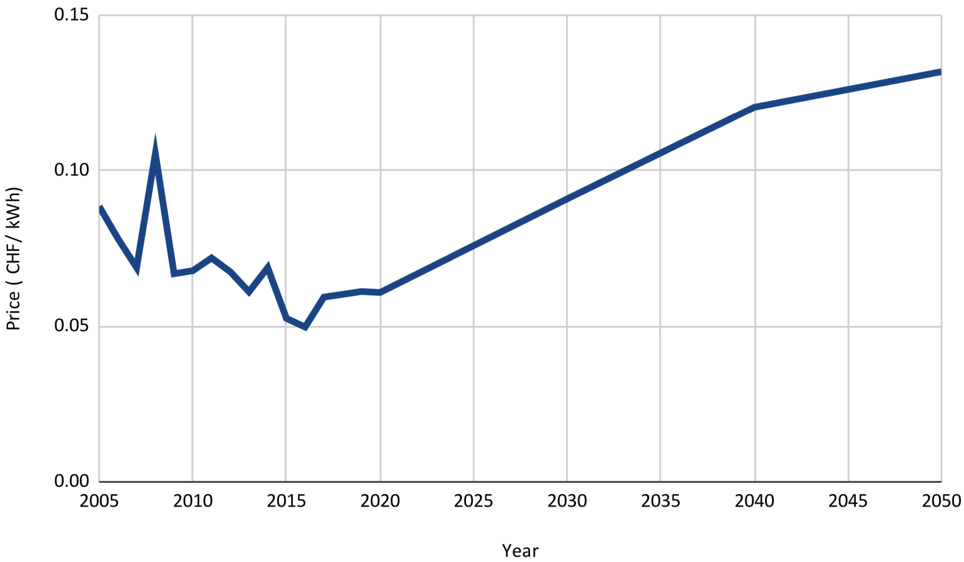


Figure B.1: Wholesale electricity prices

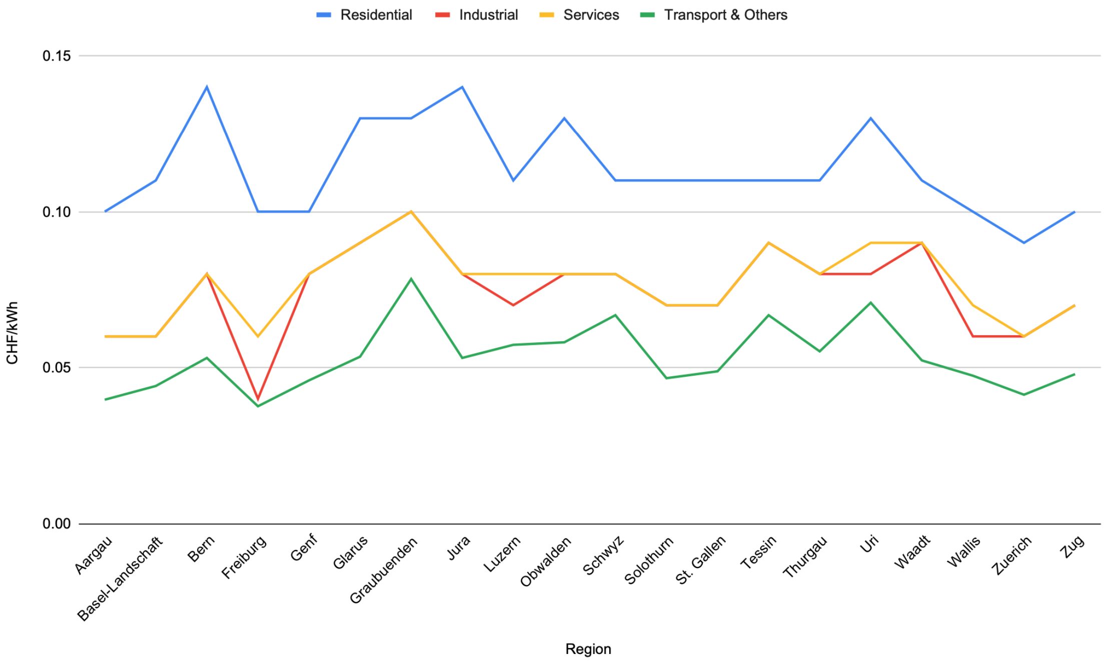


Figure B.2: Grid tariff [28]

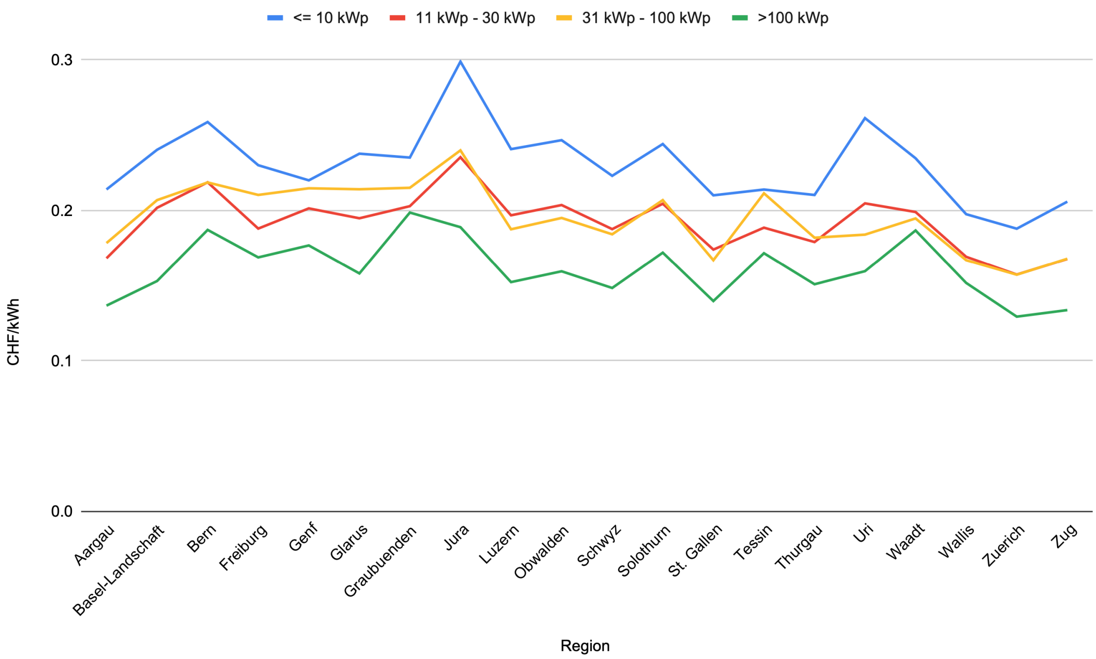


Figure B.3: Wholesale-to-retail price margin [28]

Reduktionsfaktoren Solar-wärme, Dachneigung >10°

Tabelle der Faktoren für Dachneigung >10°)

GKAT	Steildach Neigung > 10 Grad Solarthermie Anteil Kollektorfläche 2) zur theoretischen Gesamtdachfläche 1)		
	Dachfläche < 300 m2	Dachfläche 300-1000 m2	Dachfläche ≥ 1000 m3
	Anteil	Anteil	Anteil
EFH (GKAT = 1021)	0.3	0.3	
MFH (GKAT = 1025)	0.3	0.3	0.3
Gebäude mit Wohn-Nebennutzung Schulhäuser, Gewerbegebäude, etc. (GKAT = 1030)	0.3	0.3	0.3
Gebäude ohne Wohnnutzung Scheunen, Gewerbe, Industrie, etc. (GKAT = 1010, 1040, 1060, 1080)	0.3	0.3	0.3

Abbildung 3 Reduktions-faktoren Solarwärme, Dachneigung >10°

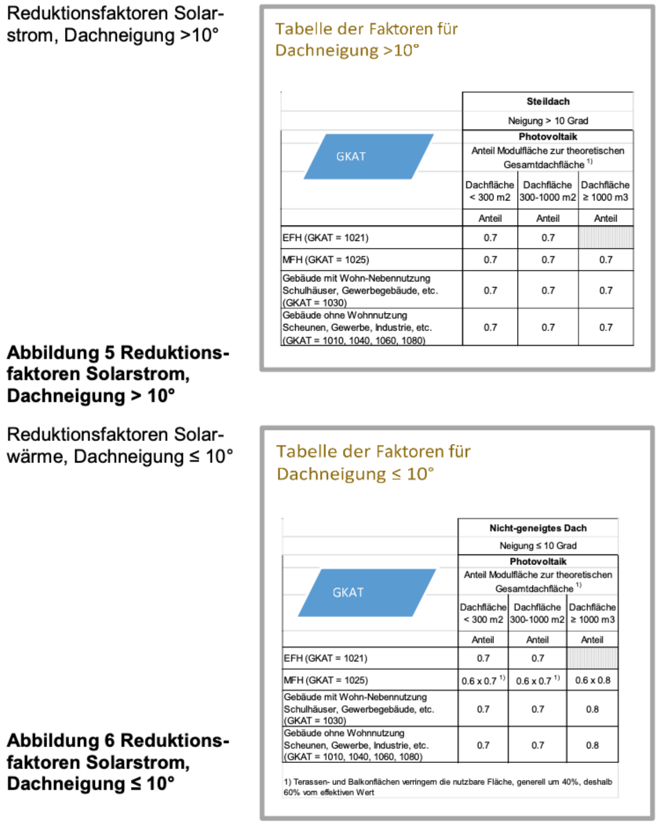
Reduktionsfaktoren Solar-wärme, Dachneigung ≤ 10°

Tabelle der Faktoren für Dachneigung ≤ 10°

GKAT	Nicht-geneigtes Dach Neigung ≤ 10 Grad Solarthermie Anteil Kollektorfläche 2) zur theoretischen Gesamtdachfläche 1)		
	Dachfläche < 300 m2	Dachfläche 300-1000 m2	Dachfläche ≥ 1000 m3
	Anteil	Anteil	Anteil
EFH (GKAT = 1021)	0.4	0.3	
MFH (GKAT = 1025)	0.4	0.3	0.3
Gebäude mit Wohn-Nebennutzung Schulhäuser, Gewerbegebäude, etc. (GKAT = 1030)	0.4	0.3	0.3
Gebäude ohne Wohnnutzung Scheunen, Gewerbe, Industrie, etc. (GKAT = 1010, 1040, 1060, 1080)	0.4	0.3	0.3

Abbildung 4 Reduktions-faktoren Solarwärme, Dachneigung ≤ 10°

Figure B.4: Adjustment factors depending on tilt and roof size [47]



Reduktionsfaktoren Solar-strom, Dachneigung >10°

Tabelle der Faktoren für Dachneigung >10°

GKAT	Steildach Neigung > 10 Grad **Photovoltaik** Anteil Modulfläche zur theoretischen Gesamtdachfläche 1) Dachfläche < 300 m2	 Dachfläche 300-1000 m2	 Dachfläche ≥ 1000 m3
	Anteil	Anteil	Anteil
EFH (GKAT = 1021)	0.7	0.7	
MFH (GKAT = 1025)	0.7	0.7	0.7
Gebäude mit Wohn-Nebennutzung Schulhäuser, Gewerbegebäude, etc. (GKAT = 1030)	0.7	0.7	0.7
Gebäude ohne Wohnnutzung Scheunen, Gewerbe, Industrie, etc. (GKAT = 1010, 1040, 1060, 1080)	0.7	0.7	0.7

Abbildung 5 Reduktions-faktoren Solarstrom, Dachneigung > 10°

Reduktionsfaktoren Solar-wärme, Dachneigung ≤ 10°

Tabelle der Faktoren für Dachneigung ≤ 10°

GKAT	Nicht-geneigtes Dach Neigung ≤ 10 Grad **Photovoltaik** Anteil Modulfläche zur theoretischen Gesamtdachfläche 1) Dachfläche < 300 m2	 Dachfläche 300-1000 m2	 Dachfläche ≥ 1000 m3
	Anteil	Anteil	Anteil
EFH (GKAT = 1021)	0.7	0.7	
MFH (GKAT = 1025)	0.6 x 0.7 1)	0.6 x 0.7 1)	0.6 x 0.8
Gebäude mit Wohn-Nebennutzung Schulhäuser, Gewerbegebäude, etc. (GKAT = 1030)	0.7	0.7	0.8
Gebäude ohne Wohnnutzung Scheunen, Gewerbe, Industrie, etc. (GKAT = 1010, 1040, 1060, 1080)	0.7	0.7	0.8

1) Terassen- und Balkonflächen verringern die nutzbare Fläche, generell um 40%, deshalb 60% vom effektiven Wert

Abbildung 6 Reduktions-faktoren Solarstrom, Dachneigung ≤ 10°

Figure B.5: Adjustment factors depending on tilt and roof size [47]

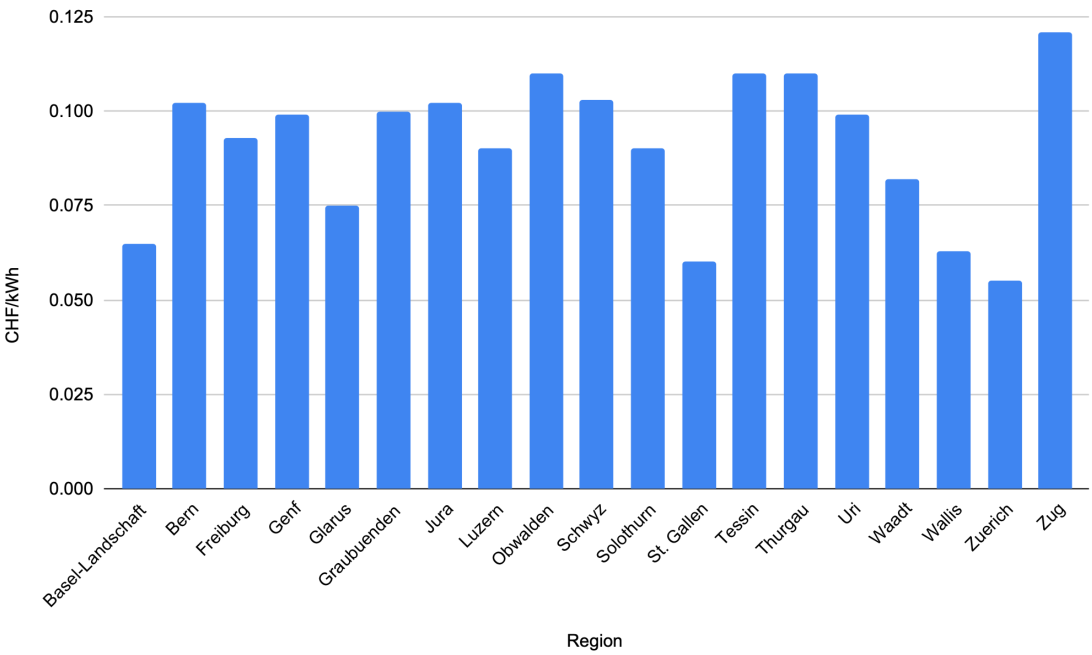


Figure B.6: Feed-in tariff [28]

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