Optimal transformation strategies for buildings, neighbourhoods and districts to reach CO₂ emission reduction targets

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Technical energy regulations are an important measure to reach climate targets. However, with recent developments in new technologies (such as decentralized energy systems, urban energy systems, energy storage systems etc.) many different options and combination of measures exist to decarbonize the building stock, which requires an update of current versions of technical energy regulations.

The aim of this work is to investigate the optimal transformation strategies for buildings and districts to reach CO₂ emission reduction targets for the Swiss building stock, to support policies and decision makers in developing new energy regulations for the future.

A simulation approach is developed, which combines clustering methods, to define representative buildings and districts, with multi-objective optimization to investigate the optimal set of building and district measures to minimize costs and CO₂ emissions. Results at building level show that the most economical measures for reaching emission targets for the future include roof retrofitting and window replacement together with PV installation. In terms of heating systems, biomass or heat pumps seem to be the most favourable option. The analysis of district archetypes shows that district level solutions are mainly applicable to urban communities, whereas building level solutions are clearly the optimal solution for rural areas.

1. Introduction

The conditioning of buildings is one of the main contributors to CO₂ emissions in Switzerland and many other developed countries. In order to comply with climate targets of the Swiss Energy Strategy 2050 [1], buildings must become more energy efficient and fossil fuel based energy systems should be replaced with efficient or renewable energy based solutions. To effectively implement these strategies, governments are responsible for identifying and implementing suitable refurbishment measures for the existing building stock, which are economically feasible, yet allow us to reach environmental targets for reduction of greenhouse gas emissions. Typical identified solutions are building level measures such as the insulation of the building envelopes, replacing windows, and installing renewable based systems such as, biomass boilers, photovoltaics, and solar thermal collectors, or efficient technologies such as heat pumps.

More recently, district or community level solutions are recommended [2], which include district heating networks, urban energy systems [3] microgrids, energy hubs [4], virtual power plants and other prosumer community groups etc. An important tool, which should guarantee the implementation of necessary changes to the building stock, are policy instruments such as technical energy regulations (TER). With more stringent requirements established by the Paris agreement, many countries have started to implement TERs in their climate mitigation actions [5]. However, with recent improvements in new technologies and increasingly stringent CO₂ targets, the existing regulations have to be revised to account for measures from the building to the district scale. Moreover effective measures, in terms of both climate reducing potential and cost effectiveness, need to be assessed for the overall heterogeneous building stock. Bottom-up modelling techniques allow us to evaluate optimal refurbishment solutions for buildings individually, and are often based on building simulation and optimization techniques [6]–[8]. Multi-criteria decision making techniques are considered where optimization objectives, based on code-based requirements such as specific energy demand requirements, CO₂ emission targets, or the share of renewable energy, are considered together with the cost-optimality [9] since one of the biggest drawbacks of efficient or renewable solutions are their relatively high investment costs.

Considering district level solutions in optimization techniques allows for assessment of whether or not a building should be connected to a district heating network and selection of the optimal energy sources, considering both decentralized and regional available energy potentials such as waste heat from combined heat and power plants (CHPs) and ambient heat from lakes and rivers. Morvaj et al. (2016) [10], for example, assessed the optimal operation and sizing of urban energy systems, in which each building is considered individually in the optimization. Wouters et al. [11] considered an optimization for a small residential neighbourhood that addressed decentralized generation, storage options, conversion technologies, and network options on the building level in order to identify key components for neighbourhood energy systems. Sensitivity analysis is also considered. Similarly, Mehleri et al. [12] used mixed integer linear programming to consider the optimization district networks including installation of technologies on the building level for a group of 10 buildings. Lastly, Omu et al. [13] optimized the installation of technologies in several interconnected district systems, including the sizes of the technologies in each node and the locations of the technologies.

With the previously mentioned methods, specific solutions for individual buildings and districts can be assessed. However, for large scale assessment of whole regions or the entire country (which accounts for thousands of buildings), a trade-off between computational costs and fidelity of the solutions needs to be accounted due to the vast number of buildings [14]. An effective method to address this issue is the use of archetypes, which group samples, such as buildings or districts, with similar characteristics into clusters [15]. Typical approaches for defining building archetypes are segmentation, classification, or statistical clustering analysis methods. The most common method that is used for buildings is a segmentation approach which categorizes buildings according to building characteristics such as age, type of building, occupancy, number of dwellings, and number of floors, and other available statistics as is done in Mata et al (2014) [16] and Montiero et al. (2015) [17]. Statistical clustering methods, such as k-means or k-medoids, can be used to select the characteristics of archetypes that most accurately represent the entire building stock. These clustering methods are used in data mining to partition the data observances, into k clusters, with each building belonging to the cluster with the nearest statistical mean. Unsupervised clustering allows the optimal number of clusters to be chosen in order to best represent the entire building stock within the archetypes. Simple classes of algorithms are distance based, i.e. they use the Euclidian distance between data points to determine which ones shall be clustered together. Another clustering method used in this work is the nearest neighbour approach. This is a hierarchical clustering method, in which each data point starts out as its own cluster and the two nearest clusters in the entire data set are then successively and iteratively united until a desired number of clusters is reached [18]. Unlike other clustering methods, this method is a deterministic method and thus will always achieve the clustering results on the same data set.

District archetypes, which take community borders as boundaries into account, are less frequently addressed in literature (e.g., [19]-[21]). However they can be used to evaluate optimal energy sources for larger areas and are useful for identifying guidelines, recommendations, or energy master plans for certain areas.

In this paper a bottom-up simulation and optimization method to evaluate optimal building and district level retrofitting and energy system selection is presented. The method allows for evaluation of typical solutions for the overall building stock of Switzerland. To address this, clustering techniques have been applied to various building characteristics of the Swiss building stock and archetypical buildings and districts have been identified. Energy consumption and renewable energy potentials have been identified for archetypical buildings and districts, and a multi-criteria optimization method has been developed to assess most optimal retrofitting and energy systems solutions for the overall building stock. These solutions can be used for identifying appropriate recommendations for TER of regions or countries, which should help in reaching future climate targets.

2. Method

The approach presented in this paper allows for the identification of typical optimal building and district level retrofitting and energy system solutions for a large building stock. The approach consists of several steps, starting from a clustering analysis. This is followed by building simulation and optimization techniques which identify optimal solutions (Figure 1). In this process, the following steps are considered. Firstly, representative archetype buildings of the overall building stock are generated through clustering methods using different data sources for building characteristics, energy demand and 3D building data. The approach is applied to residential buildings and also other building types, such as offices, hospitals, restaurants, shops, and schools.

Once the archetype buildings are identified, an urban energy simulation tool is used to identify the current energy consumption profiles from all archetypes including future scenarios, which take different envelope retrofitting interventions into account. In a third step, archetypical districts are identified which build on the archetypical buildings including their energy consumption and the current and potential future energy resource potentials. Next, an optimization model is generated which assesses the optimal retrofit solution and building or district energy system, based on a multi-objective linear optimization. The method is applied to the archetype buildings and districts of Switzerland and the optimal set of measures and systems are identified based on a multi-criteria analysis where costs and life-cycle CO₂ emissions (including grey energy of retrofit materials and installed technologies) are taken into account.

In order to consider the retrofits in districts, annual retrofit rates that are based on building construction age from the Swiss Energy Strategy 2050 [1] are taken into account. In addition, the applied retrofits for districts are based on the optimal retrofit solutions chosen in the building level cases. In a last step, a robustness analysis is performed which takes uncertainties of input parameters into account (such as changes in energy prices, system and retrofitting costs, efficiencies and changes in CO₂ values). Robust solutions for the building stock are identified, and compared to the deterministic solutions.

Figure 1 Overview figure on approach

2.1. Archetype buildings

The Swiss building stock consists of more than 1.8 Million buildings [22]. Performing building simulation and optimization for the entire building stock would be too time consuming and computationally intensive. Consequently, a reasonably small subsample of buildings can be selected that represents the whole building stock in a sufficient manner.

2.1.1. Residential buildings

Switzerland's residential building stock is composed of approximately 1.8 Million buildings, 32% of which are single family homes (SFH) and 16% of which are multi-family homes (MFH)[22]. To define representative archetype buildings, clustering techniques on various building characteristics are deployed. In order to effectively cluster, information such as building area, age of the building, energy demand, climatic region or renewable energy potential is collected. In this analysis the Swiss building stock has been condensed to 50 multi-family buildings (MFH) and 50 single-family buildings (SFH) using the nearest neighbours clustering algorithm, which selects buildings based on dissimilarity.

More explicitly, this selection algorithm operates according to the following 4 steps, which are shown in Figure 2 and Figure 3:

1. A subset of properties describing the individual buildings in the initial building stock is selected. This selection is based on the potential for identifying dissimilarities and the availability of data.

2. The n selected properties allow for a representation of the buildings in an n -dimensional feature space, in which each selected property defines one dimension. The location of each building in the feature space therefore depends on the value of its properties.

3. The feature space is then standardized based on the following equation:

$$f_{j,std}^i = \frac{f_j^i - \bar{f}^i}{\sigma_{fi}}, \quad \forall i \in \{1, \dots, n\} \text{ and } \forall j \in \{1, \dots, m\} \quad (1)$$

where f_j^i is the i th feature of the j th building. n and m are the total number of features and buildings used in the selection algorithm, respectively. $\bar{f}^i$ refers to the mean of the i th feature across all buildings and σ_{fi} is the corresponding standard deviation. Standardising the feature space is necessary in order to treat dissimilarities equally across all features in the next step.

4. In this last step, buildings are removed from the initial building stock based on their similarity to other buildings. Mathematically, the similarity of two buildings can be represented by their proximity in the standardised feature space. Therefore, the nearest neighbour of each building in the feature space can be viewed as the building it is most similar to. The building with the closest nearest neighbour is therefore iteratively removed from the initial building stock since it presents the highest similarity to another building. This iterative process is repeated until the remaining building stock reaches the desired size.

Figure 2 Selection and standardization of building properties (features in the feature space) as performed in steps one to three of the selection algorithm. The black dots represent the values of the respective properties of all buildings in

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the initial building stock.

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Figure 3 Iterative determination of nearest neighbours in the feature space and removal of the building with the closest nearest neighbour from the remaining building stock. (Step 4 of the selection algorithm)

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In this analysis, data from the Building and Apartment Registry (Gebäude und Wohnungsregister or GWS) from the Swiss Federal Office for Statistics (BFS) [22], the Swiss Federal Office for Topography (swisstopo) [23] and the Swiss Competence Centre for Energy Research (SCCER) [24] are consolidated to form the initial building stock used by the above mentioned algorithm. The combined database provides detailed information on approximately 230'000 MFH and 400'000 SFH, i.e. approximately 35% of the Swiss building stock. The exact building properties selected from these data sources are shown in Table 1.

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The subset of properties, which were deemed to be most relevant to the selection of archetype SFH, are the district's location, floor area, building height, construction period, energy carrier for heating, energy carrier for hot water, and number of residents. In addition to these properties, the number of dwellings in each building is used in the selection of archetype MFH.

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Due to the very large data set used for clustering in this approach, this method is particularly effective since it is deterministic and will result in the same set of clustering solutions every time it is run. Other clustering methods, such as k-means or medoids, take very long times to run for large data sets and due to the number of residential buildings, the nearest neighbour clustering method was preferred.

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Table 1: Features available at a building-level and their corresponding sources

Features	Databases by:		
	BFS	SCCER	swisstopo
GIS building code			×
Identifier of municipality	×	×	×
Identifier of canton	×	×	×
Postal code	×		
Building coordinates	×	×	×
Classification of construction zone			×
Building category BFS	×		
Building category SCCER		×	
Number of dwellings in building	×		
Number of residents	×		
Number of main residents	×		
Construction period	×		
Number of floors	×		
Building height			×
Ground floor area			×
Total floor area		×	×
Estimated total heated surface		×	
Heating system	×		
Energy carrier for heating	×	×	
Availability of hot water	×		
Energy carrier for hot water		×	
Heating demand		×	
Domestic hot water demand		×	
Final energy demand for heating& domestic hot water		×	

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188 This clustering approach is applied on the selected SFH and MFH buildings, and the resulting
 189 archetypes are used for identifying relevant measures. The building categories and the reference heating
 190 energy systems for all archetypes are shown in Figure A1. In Figure A1, it is shown that the majority of
 191 buildings are from the period of 1949-1994 and 77% of the archetype buildings still use either an electric,
 192 oil, or gas boiler which leaves significant room for improvement of the building stock. The locations of
 193 the representative buildings in Switzerland are shown in Figure 4.

194 2.1.2. Non-residential

195 Non-residential buildings in Switzerland are registered in the General Classification of Economic
 196 Activities (NOGA) database, which assigns to each building a business category [25]. The most prevalent
 197 business categories that utilize both heating and electricity demand are selected, and assigned to the
 198 archetype categories shops, offices, restaurants and hotels, schools and hospitals [26]. In a next step, the

non-residential building stock was assigned to these categories and the floor area, building height and building age of all buildings, based on the GWS database [22] was used for the k-medoids clustering analysis. K-medoids is a clustering method, which clusters based on minimization of the distance between points in a cluster and the determined centre of that cluster. This method was chosen over the nearest neighbour clustering method that was used for the residential buildings, as there are fewer data observations with the non-residential buildings and thus a more computationally intensive method could be used. The clustering resulted in 45 archetype buildings for the non-residential building stock, which are summarized in Table 2.

Table 2 Identified non-residential archetypes

Building category	Nr of Archetypes	Total number of buildings represented
Restaurants	9	6380
Schools	9	2115
Hospitals	9	4453
Offices	9	11202
Shops	9	7512
Total	45	31662

Figure 4 Residential building archetypes, 50 single-family houses (SFH), and 50 multi-family houses (MFH)

2.2. Building energy demand, solar potential and retrofitting solutions

2.2.1. Building energy demand

Energy demand calculations for archetypal buildings are performed using the tool CESAR "Combined Energy Simulation and Retrofitting" [27]. This tool utilizes the building simulation engine EnergyPlus [28] to calculate hourly electricity and heat demand profiles of buildings within a district over a period of one year. Geo-spatial information (GIS data) pertaining to building floorplans and their height (2.5D shape information) is used to represent the geometry of buildings. Neighbouring buildings are considered as shading objects in the model. Additional input information for the simulations pertains to age, type, and the primarily used energy carriers for space heating and domestic hot water. Internal conditions pertaining to occupancy, appliances, domestic hot water (DHW), heating set-point temperature, cooling set-point temperature, activity levels, and lighting patterns are taken from SIA 2024 (2015) [29]. Energy carriers for heating and DHW are required for the conversion of energy demand into energy consumption. Furthermore, information on energy carriers used by individual buildings is used to determine its energy related emissions. Hourly energy demand calculations are performed for all archetype buildings for a full year (8760 hours), and weather conditions of the different climatic regions are represented by 54 weather files (taken from Meteonorm [30]) based on SIA 2028 climate regions [31]. This data is stored in a database and is later used for the analysis of building and district level solutions.

The initial constructions for building age (without retrofit), for both original constructions and retrofitted constructions are shown in Table 3. The constructions preceding 1994 are based on the Insti-

tut für Bauforschung [32]. Constructions from 1994-2007 are taken from the Bauteilkatalog [33] combined with typical insulation thickness values from Jakob (2008) [34]. For new buildings (>2010) and retrofit constructions, the minimum (Grenzwerte) insulation thicknesses according to SIA380/1 are used [34].

Table 3 U-value (W/m-K) of age dependent constructions used in the CESAR tool (non-retrofitted or original constructions and the constructions with insulation added during a retrofit)

Construc- tion period	Walls		Roof		Floors		Windows	
	Original	Retrofit	Original	Retrofit	Original	Retrofit	Original	Retrofit
≤1918	1.645	0.243	0.752	0.236	0.765	0.243	5.778	1.06
1919-1948	1.509	0.244	0.745	0.249	0.971	0.239	5.778	1.06
1949-1978	1.259	0.233	0.856	0.248	0.778	0.254	3.126	1.06
1979-1994	0.46	0.239	0.392	0.24	0.706	0.246	1.668	1.06
1995-2001	0.268	0.215	0.289	0.22	0.336	0.248	1.652	1.06
2002-2006	0.222	0.161	0.245	0.161	0.91	0.291	1.407	1.06
2007-2009	0.211	0.155	0.206	0.161	0.252	0.18	1.3	1.06
2010-2014	0.2	0.14	0.186	0.14	0.232	0.2	1.06	0.927
>2014	0.17	0.14	0.17	0.14	0.211	0.2	0.927	0.927

2.2.2. Solar potential

The solar potential of roof surfaces of all archetype buildings were computed using EnergyPlus. The simulation engine EnergyPlus calculates radiation on a sloped surface based on solar radiation information from the weather files of the location, and roof geometry derived from Swisstopo [23] such as the roof orientation and inclination. Subsequently, the solar incident on the sloped roof surfaces is computed for every hour of the year. North facing roof surfaces are excluded from the analysis. The total south oriented roof surface available for PV installation is further reduced to 60% to account for additional non-useable areas such as chimneys or other roof obstructions [36]. The solar potential of individual building archetypes are stored in the database to be further used for the analysis.

2.2.3. Retrofitting solutions

An additional module of CESAR allows for evaluation of different partial envelope retrofits and other energy efficiency measures in addition to the current energy demand of the buildings. Using this module, envelope measures, such as insulating different surfaces or replacing windows, can be evaluated. In case of retrofitting existing construction elements, the original archetypical constructions per building age are modified with insulation added in order to meet the minimum insulation thickness set by current energy efficiency standards (SIA 380/1) [34]. For the analysis a set of retrofitting interventions (as per Table 4) are considered.

Table 4 List of investigated measures

Considered measures at building level	
Envelope interventions	Roof insulation
	Wall insulation
	Replacement of windows
	Ground floor insulation
	Window replacement and wall insulation
	Full retrofitting

255 **2.3.Archetype districts**

256 To evaluate potentials for district level solutions, the k-medoids clustering method was used to
257 classify existing communities of different sizes, with different building densities, and with different re-
258 newable potentials for renewable energy into urban, suburban and rural categories. In order to cluster
259 the buildings, the following methodology is used:

- 260 1. The location of each building in the commune registry of Switzerland (from the GWS data
261 set) is identified [22].
- 262 2. Next, the overall map of Switzerland is structured into cells of 1 km by 1 km (see Figure 5).
263 Raster cells where no buildings are located are ignored. For every raster cell, the total
264 floor area of buildings within this raster cell is aggregated for every cell using ArcGIS.
- 265 3. The resulting density values are then clustered into high, medium and low-density raster
266 cells based on the percentage of the communes (Gemeindes) in Switzerland that are clas-
267 sified as rural, suburban, and urban by the Swiss Federal Buro for Statistics data analysis
268 on Spatial Divisions [37]. Using these percentages, the raster cells are sorted by density
269 and are classified into three clusters that reflect rural, suburban, and urban by raster cell
270 rather than Gemeinde. Please refer to Figure A2 in the appendix for the histogram of
271 raster cell density and the corresponding cluster divisions. Switzerland consists of 2222
272 communities of different sizes [22], in which each community is made up of these raster
273 cells.
- 274 4. District archetypes are then extracted. Following the classification approach, a k-medoids
275 clustering algorithm divides the three groups of districts into four respective clusters
276 based on a matrix. This matrix includes different characteristics obtained at building level.
277 The clustering algorithm takes into account building types (SFH, MFH, offices, etc.), age
278 of the buildings, as well as the community based renewable potential. Information on

renewable potential, pertaining to solar potential on roof surfaces is taken from the building data base (as described in section 2.2.2). Biomass (wood chips and pellets) and waste potential (including manure and waste) were taken from Yazdanie (2017) [38].

The clustering analysis resulted into the three categories (urban, suburban and rural) in which each category contains 4 archetypes (summarized in Table 5 and displayed in Figure 6). Resulting assumption on renewable potential and building information is summarized in Figure 7.

Figure 5 Raster cells of high, medium or low-density

Table 5 District level archetypes

		Communities represented by archetype							
		Nr of raster cells							
		Inhabit-ants.	high	med	low	%	Nr	%	Nr
Urban	Rheinfelden	11290	897	13	11	51	45	4	89
	Frauenfeld	25297	836	1892	257	25	22		
	Basel	171017	3677	53	0	19	17		
	Grenchen	16728	1393	715	18	5	4		
Suburban	Täuffelen	2537	0	548	9	45	320	32	711
	Beringen	3374	266	276	42	25	178		
	Meiringen	4489	0	681	182	18	128		
	Gossau (ZH)	9397	39	630	176	12	85		
Rural	Thörigen	1016	0	189	11	37	526	64	1422
	Grandval	333	0	59	34	31	441		
	Tobel-Tägerschen	1378	0	285	24	20	284		
	Endingen	1957	0	213	61	12	171		
						300	2222	100	2222

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289 *Figure 6 Representation of communities belonging to each cluster. Green represents rural districts, yellow represents*
290 *suburban districts, and red represents urban districts.*

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Figure 7 Renewable potential and building type and age of archetype districts.

The energy demand profiles (electricity and heating) for residential and non-residential buildings of the above-mentioned archetype districts are calculated using the archetype building energy simulation database and fitted to the actual building's square area encountered in each typical district. The energy demand is then calculated for two different scenarios, in which it is assumed that building envelopes are retrofitted at different rates. For the two future scenarios, the optimal building retrofit selections from the building optimizations (which will be described in section 2.4) are used. This allows for assignment of optimal retrofitting solutions (e.g. replacement of windows, façade retrofitting, etc.) for every building within the district. In order to apply the appropriate partial retrofit, building level optimal Pareto front solutions for the targets between $10 \pm 2 \text{ kg CO}_2/\text{m}^2$ are used. Since our average target for the buildings is set to be in the range of $10 \text{ kg CO}_2/\text{m}^2$, as specified by SIA 2040 [39], we chose to use uncertainty bounds of plus or minus 20% to provide a greater range of solutions with an average of approximately $10 \text{ kg CO}_2/\text{m}^2$. In order to account for retrofitting rates per year, two different scenarios are considered which include the business as usual scenario (BAU) with an average retrofitting rate of 1% and the new energy policy scenario (NEP) with average retrofitting rate of 2.5% according to the Swiss energy strategy 2050 [1]. The actual retrofit rates are set by the age of the building and the year of consideration that are found in the energy strategy itself are shown in Table A5. The applied partial retrofit rates are shown in Table A6. Future scenarios are calculated for the years 2035 and 2050 (so BAU 2035, BAU 2050, NEP 2035 and NEP 2050). Figure 8 shows the energy demand for the district archetypes under the different scenarios. The retrofitting rates and solutions classified based on the scenarios, building ages and types are illustrated in Table A5 and the recommended partial retrofit rates are shown in Table A6.

Figure 8 Comparison of aggregated loads for Reference scenarios - BAU and NEP scenarios for years 2035 and 2050.

2.4. Building and district system optimization

In order to identify most promising retrofitting strategies (for both the building envelope and energy supply systems) an optimization tool based on the energy hub approach is utilized. The approach is based on mixed-integer linear programming optimization [40]. To identify multi-objective (cost and life cycle CO₂ emissions) optimum solutions the epsilon constraint method is deployed [41] to generate 10 Pareto solutions which minimize the two objective functions: cost and life-cycle CO₂ emissions. The generated energy demand profiles, together with existing energy supply options (grid electricity, natural gas, oil, heat pump or district heating), renewable energy potentials (such as solar, biomass or ground source heat) of individual buildings are taken as input to the model. Demand profiles are further processed to identify typical days and peak days, which are then used in order to reduce the horizons for the optimizations. This process is called the typical days method and is described in Marquant et al. (2015) [42]. Six typical days were assumed using this methodology and three peak days (one for electricity, one for heating, and one for solar radiation) were assumed. Additionally, system options, which are mentioned in Table 2, are implemented into the optimization framework, which pertain to biomass boilers, micro combined heat and power plants (CHP), air source heat pumps (ASHP), ground source

heat pumps (GSHP), photovoltaic panels (PV), solar thermal collectors (ST), oil, and gas boilers as conversion technologies. Hot water thermal storage tanks and batteries are also included as storage technologies. The building envelope retrofitting scenario and energy efficiency measures are implemented as additional decision variables within the optimization framework. The resulting energy hub configuration is depicted in Figure 9.

Figure 9: Layout of the energy hub optimization with included technologies for building and district energy systems as well as building envelope-retrofitting options.

2.4.1. Building level system assumptions

For the building level optimization, the typical buildings were simulated considering the selected measures for implementation. This optimization focused on the optimal combination of heating system selection and retrofit update. For the retrofit, the buildings were simulated with seven different retrofit choices: no retrofit (the reference case), roof retrofit, ground retrofit, façade retrofit, window retrofit, combined façade and window retrofit, and a full retrofit including all partial retrofit options. The costs and embodied emissions (EE) of all retrofit types are calculated with the CESAR tool for each building depending on the building specific roof, window, façade, or floor area and are imported into the optimization. A binary value is allocated for each retrofit option with the requirement that either only one retrofit option can be selected. The buildings can choose to keep their current heating system (typically oil boilers, gas boilers, electric boilers, heat pumps, or biomass boilers) or they can update their heating system to a new gas boiler, a micro combined heat and power system, a ground source heat pump (GSHP), and air source heat pump (ASHP), or a new biomass boiler. Although any type of heating system can be installed, there is a requirement in the model that a heat pump can only be installed in old buildings (<1994) with an upgrade of the facade or with underfloor heating. Since heat pumps deliver water to buildings at lower temperatures than boiler systems, it is recommended that heat losses through the facade are reduced before the installation of a heat pump [40]. In addition, depending on the commune of the building, a restriction on the biomass potential (based on the available wood resources on the community level) is implemented [43]. This restriction is calculated in terms of kWh of

wood chips or pellets/year/m² and is based on the available wood resources in the community [38] and the total heated floor area in the commune [22].

The rooftop area available for installation of solar technologies is also assessed and either photovoltaic panels or solar thermal panels can be installed. The combined area of the PV panels and the ST panels must be less than or equal to the maximum area allowed on the roof, which was defined in Section 2.2.2. Finally, storage technologies, such as thermal storage and battery storage are also considered.

The location dependant and retrofit dependent building loads are then imported into the optimization with the solar profiles, the technology cost and performance data, and the embodied emissions of the technologies, and optimal combination of measures are determined. Details on the energy carrier prices and carbon factors (including grey emissions) can be found in Table A1 and details on the technology capital costs (fixed and linear), the embodied emissions (fixed and linear) the technology performance data, the lifetimes of the technologies can be found in Table A2. The different partial retrofit costs and embodied emissions are calculated based on the assumptions in Table A2.

2.4.2. District level system assumptions

The district scale energy hub model considers the possibility of installing building and district scale systems, taking into account the economies of scale and differences in systems efficiencies based on the installed system scale. A constraint is added that ensures that district heating networks are only allowed in high density raster cells and within half of the medium raster cells. The deployment of the district heating network is a decision variable within those boundaries. The capacity and the losses of the district heating network depend on the total number of buildings connected to the network and on the average distance between buildings interconnected in the district heating network. The average distance between buildings connected is computed by solving the minimum spanning tree problem for each district; thus predicting the total length of potential network if fully deployed and the average distances between neighbourhood buildings. In order to solve the optimization problem, the model includes a formulation for linearizing quadratic equations.

The following assumptions are formulated at the district scale level for the optimization model:

- The technologies such as boilers (wood, waste, biomass, and gas), heat pumps (GSHP, ASHP) and CHP (wood, waste, gas) can supply both the low temperature district heating network (LTDH) and the high temperature heating network (HTDH). Therefore, they are specified twice in the technology list.
- The boiler and CHP technologies which supply to the LTDH and HTDH network have the same costs and efficiencies in both cases.
- Waste as a fuel is assumed to have an emission factor of 3 g CO₂/kWh [44]
- Fixed and linear costs and embodied emissions have been accounted for in the model for each technology at the building and district scale (please refer to Table A2 for more details)
- Only buildings in dense and medium rasters can be supplied through both district scale and building scale energy systems.

- Constraints are added for the availability of biomass and waste for building level and district level systems; biomass potential being wood potential and waste including both manure and other types of waste.

2.5. Robustness analysis

The preceding methodology seeks to identify optimal building and district retrofitting solutions in a deterministic manner by assuming perfect knowledge of all relevant model input parameters. However, in reality, this is very rarely the case and most model parameters should be treated as uncertain. This can be either because some model parameters are inherently stochastic (e.g. energy demand patterns, which are in turn affected by stochastic occupant behaviours, weather patterns, climate change etc.) or because it is extremely difficult to acquire perfect knowledge about them (e.g. regarding future energy carrier and technology prices).

Neglecting these uncertainties entails the risk of suboptimal solutions in cases when the actual values of the model parameters are different from the ones assumed during the design stage. As a result, this section aims to, firstly, categorize the most important uncertain parameters of the energy hub model and, secondly, to identify optimal building retrofit solutions that are robust against uncertainty.

The methodology for this is summarized in Figure 10. Instead of single values for the model input parameters, probability distributions are used in the stochastic analysis to describe the model's uncertain input parameters. Then we draw multiple samples for the probability distributions and we perform Monte Carlo simulations by executing the energy hub model for each sampled set of values. The outcome of this analysis is a set of Pareto optimal solutions for different possible realisations of uncertainty. Then by examining and analysing the variations of the model output, we can identify the most robust solutions i.e. the solutions that emerge most often in the resulting Pareto fronts.

Figure 10 Methodology for stochastic Monte Carlo analysis.

Model parameters, which are treated as uncertain in this analysis, are summarized in Table 6. Various sources are used to assign probability distributions to the model's uncertain parameters including a PhD thesis by Mavromatidis (2018) [45] and the Swiss Energy Strategy 2050 [1], while in some cases, due to the lack of reliable sources, we rely on our own estimates to assign probability distributions to the uncertain model parameters.

During this process, special attention was paid to ensure that the chosen probability distributions capture the uncertain characteristics of each parameter. For instance, the probability distributions of the energy demands reflect the fact that besides the uncertainties caused by the building occupants, heating demands are projected to most likely decrease because of climate change impacts, while the reverse is

true for cooling demands. Similarly, regarding the investment costs of energy technologies, the probability distributions capture both the uncertainty due to inaccurate estimates of technology costs and due to the possibility of technology developments changing the costs of energy technology in the future. Moreover, the distributions reflect the fact that the costs of mature technologies, like gas or oil boilers, will most likely not reduce in the future, while for others, such as PV panels and batteries, aggressive cost reductions are a considerable possibility. As a result, the probability distributions of less mature technologies are more skewed towards lower future costs, while for mature technologies the probability distributions indicate equal probabilities of higher and lower costs than today. The list of the uncertain parameters along with the probability distributions used for them are given in Table A4 of the Appendix.

The stochastic analysis is performed for 50 SFH, 25 MFH considered and for each building 50 Monte Carlo simulations with different values for the input parameters are performed.

Table 6. List of uncertain model parameters

Uncertain model parameters

Building energy demands (heating, cooling, electricity demands)

Solar radiation patterns

Energy carrier prices (electricity, natural gas, oil, biomass) – CHF/kWh

Energy carrier emission factors (electricity, natural gas, oil, biomass) – gCO₂/kWh

Investment costs for generation & storage technologies

Embodied emissions for generation & storage technologies

Investment costs for retrofit interventions

Embodied emissions for retrofit interventions

Technical characteristics of energy generation and storage technologies

3. Results and discussion

3.1. Building interventions

Building envelope interventions

For the 50 archetypes, the current energy demand for space heating, domestic hot water, and electricity is calculated using the CESAR tool. Additionally, different retrofitting building envelope scenarios are examined which pertain to roof, ground, or wall insulation or a change in windows or a combination of those measures. The distribution of resulting heating loads of the different age categories of buildings in all 54 weather stations, according to SIA 2028 [31] in Switzerland are shown in Figure 11. This Figure shows that in the non-retrofitted state of the buildings, the distribution of energy demand is much more pronounced compared to buildings, which are already retrofitted. This effect is demonstrated significantly in older buildings versus newer buildings. The most effective individual envelope interventions are the insulation of roofs or change of windows, which shows that end energy demand, can be reduced within a range of 20 to 30%. The resulting energy demand of building envelope-retrofitting interventions can be examined in this way, however the optimal selection of each measure to reach CO₂ targets, when combined with a heating system change, is difficult to extract. In a next step, the demand reduction, retrofit costs, and retrofit embodied emissions are used as input information in the optimization.

Figure 11 Violin plots of the distribution in energy consumption for different retrofitting scenarios per age class of SFH and for 54 weather station profiles in Switzerland (over 18,200 individual runs)

Optimal retrofitting measures

To evaluate optimal building retrofitting measures, the optimization framework for building envelope and system interventions as described in section 2.4 is deployed. In the optimization, the optimal retrofit and systems selections are chosen according to the multi-objective function: one retrofit option, one heating system, an optional PV or ST solar system, and options for thermal and battery storage are

chosen. Due to the long computational time of the model for the robust solutions, the analysis is conducted for a subset of 50 SFH and 50 MFH archetypes, which represent 75% of all buildings in the residential building sector and additionally for the non-residential archetype buildings. The multi-criteria analysis for costs and CO₂ emissions results in 10 Pareto optimal solutions. Figure 12 shows the average Pareto fronts for SFH, MFH and non-residential buildings.

Each point in these curves represents the average of the Pareto points for the resulting solutions. It is interesting to see that solutions for MFH are significantly cheaper in terms of costs and CO₂ emissions, followed by schools and office buildings. This is due to economies of scale for larger buildings which reducing the relative costs for retrofits and system installations per m² and kW respectfully... Figure 13 shows the distribution of the optimal building envelope interventions (top graphs) and building systems (bottom graphs) based on of the resulting CO₂ values. The resulting optimal heating systems show a shift from fossil fuel based heating systems (such as oil or gas boilers) in solutions favouring a cost minimization to renewable based systems such as biomass boilers and photovoltaic panels, and highly efficient technologies like air-source heat pumps for solutions favouring CO₂ emission minimizations. ASHPs are generally favourable to GSHPs due to their lower costs, even though GSHPs have higher efficiencies. It can be seen that in the case of SFHs, the most prevailing heating system selection pertains to biomass boilers, whereas for MFHs mainly ASHP are selected. This is due to a restriction of availability in the biomass potential for individual buildings.

Switzerland would like to reduce its CO₂ emissions until 2050 to one fourth compared to current emissions, which shall act as a basis to reach the goals of the 2000-Watt society in the building sector [46]. The targets under this regulation include grey energy and grey emissions, as is done in this work. In order to achieve this, overall CO₂ emissions should be reduced to an average of 10 kg CO₂-eq/m² for construction and operation of retrofitted buildings [39]. This goal would be achieved with the first two solutions shown in Figure 13. In this Figure, it is seen that many buildings require significant measures to meet the targets set for buildings as the cost optimal solutions in all cases will miss the targets. The cost for offsetting CO₂ emissions to meet the targets (< 10 kg CO₂-eq/m²) is in the range of CHF 200/kg CO₂-eq for MFH and CHF 420/kg CO₂-eq for SFH. Shops and restaurants were the most difficult building to decarbonize in this case study due to high energy demands.

Figure 14 shows additionally, for all Pareto points and archetypes, the system and envelope retrofitting selection and the CO₂ emissions that result from the selected combination. As can be seen from this Figure, system solutions that reach the target are mainly ASHP and biomass boilers, only few buildings, which have an oil or gas boiler installed, are able to reach the 10 kg CO₂-eq/m² threshold. However, in terms of envelope retrofitting optimal, the solutions differ quite significantly and range from no retrofitting to full retrofitting of the building envelope. These results show clearly that the optimal solution depends significantly on the initial state of the building and its boundary conditions.

Figure 12 Average Pareto front for single family, multi-family and non-residential buildings, representing the Swiss building stock. The life-cycle emissions represent annualized CO₂ emissions over the lifetime of the components used and their operation.

Figure 13: For the top 50 single-family homes and multi-family homes, the optimal retrofit and technology selection is determined. The solutions are grouped by their CO₂ emissions. Similar figures including non-residential buildings can be found in Figure A4 and A5 in the Appendix

Figure 14 Distribution of Pareto optimal solutions for 50 SFH and 50 MFH archetype buildings depending on their CO₂ emissions.

From all results which reach the emissions level between 8-12 kg CO₂ eq/m², the combination of optimal measures are selected which have the highest frequency within the 500 results for all buildings (50 buildings and 10 optimal solutions per building result in 500 optimal points). These are shown in

Table 7 for SFH and MFH. The set of six identified solutions are applicable to 68% of all solutions that fall inside the recommended CO₂ target range. Identified measures pertain to roof retrofitting or window replacement and façade insulation together with PV installation. A battery is selected for about 8% of solutions in MFH and 7.7% of solutions in SFH. In terms of heating systems, biomass seems to be the most favourable option for SFH, while ASHPs can also be attractive, particularly for MFH.

Table 7 the identified most significant measures for SFH and MFH for the deterministic solutions

Deterministic Solutions				
MFH				
Envelope retrofit type	Heating system	Solar system	Battery	Share
Window-wall	ASHP	PV	✗	41.3%
Roof	Biomass	PV	✗	8.15%
No retrofit	ASHP	PV	✗	6.27%
Window	ASHP	PV	✗	5.01%
No retrofit	Biomass	PV	✓	4.07%
No retrofit	ASHP	PV	✓	4.07%
				69%
SFH				
Envelope retrofit type	Heating system	Solar system	Battery	Share
Roof	ASHP	PV	✗	25.5%
No retrofit	ASHP	PV	✗	19.3%
Window-wall	GSHP	PV	✓	7.72%
No retrofit	Biomass	PV	✗	5.02%
Roof	Biomass	PV	✗	4.25%
Window-wall	ASHP	PV	✗	4.25%
				66%

Robustness results

To illustrate the effects that uncertainty can have on our analysis, Figure 15 contrasts the Pareto front of optimal solutions resulting from the deterministic model to the Pareto fronts resulting from the Monte Carlo analysis for a sample building. It can be observed that while the trends in the deterministic and the stochastic case are similar, the stochastic analysis results reveal that the actual economic and carbon performance of the optimal solutions can vary widely and might be significantly different than the one predicted by the deterministic analysis. Hence, it is crucial that such a stochastic analysis is performed.

Figure 15 Comparison of deterministic Pareto front with multiple stochastic Pareto fronts resulting from the Robustness analysis.

Following the economic and the environmental performance of the optimal solutions, it is worthwhile to investigate the variations in terms of the optimal retrofit interventions and energy system changes resulting from the Monte Carlo simulations. Starting from the first aspect, Figure 16 presents and contrasts the optimal retrofit measures from the deterministic and the stochastic analysis¹.

At a first glance, the plots in the deterministic and the stochastic case might appear similar for both the SFH and the MFH building categories, which is a testament to the quality of the deterministic model, which is able to capture the same trends as the more robust, stochastic model. However, there are some important differences to note. Starting from the SFH category across all of the CO₂ emission brackets, the stochastic result show a more balanced allocation for retrofit interventions. For instance, in the stochastic results, window retrofits are present with an important share in all emission brackets, while in the deterministic results the percentage of window retrofits vary more for the different brackets. Regarding the specific solutions that are below the CO₂ target of 10 kgCO₂/m², the share of the “No retrofit” solutions are higher in the deterministic case compared to the stochastic case, with the latter also showing an increased importance of “Full” and “Window-wall” retrofits in order to achieve the targets.

The results for the MFH category exhibit similar patterns. For instance, in the deterministic case and for emissions above 20 kgCO₂/m² the “Roof” and “Window” retrofit options are dominant. On the other hand, in the stochastic case, a more balanced allocation of solutions is observed with “Wall” and “Window-wall” retrofit solutions also appearing in the optimal solution mix. For solutions below the CO₂ target of 10 kgCO₂/m², the stochastic results exhibit an increased importance of “Full” retrofits and a decreased importance of “Roof” retrofits compared to the deterministic case. Thus, it can be concluded that considering all possible realizations of the uncertain parameters, such as building energy demands, retrofit and technology costs and embodied emissions, and energy carrier prices and emission factors, deeper building envelope retrofits might be necessary in order to achieve the desired CO₂ emission targets.

¹ Note that the plots for the deterministic and the stochastic cases summarize the outputs for the same set of buildings; nevertheless, fewer buildings were used in the stochastic case (due to the computational requirements of the robust model), thus the deterministic plots are not identical to the ones presented earlier

Figure 16 Comparison of optimal building envelope retrofit solutions of the deterministic and the stochastic models for SFH and MFH building categories. The retrofit solutions are grouped in emission brackets according to the CO₂ emissions that they achieve and they are reported in terms of the share of each retrofit intervention out of all solutions in each emission bracket.

Similarly, Figure 17 presents the corresponding results of the deterministic and the stochastic analysis results regarding the optimal energy system selections for the SFH and MFH building categories. Two main patterns that can be observed for both building categories. The first is that at high emission levels (above 15 kgCO₂/m²) result from a dominance of oil and gas boilers. This can be observed in both the deterministic and the stochastic results, while only a small part of the total capacity is attributed to photovoltaic and solar thermal technologies. This is to be expected, since at high emission levels, these two boiler technologies with their relatively lower costs, offer an affordable energy system solution for both building types.

The second pattern is observed for solutions that are below the target CO₂ value of 10 kgCO₂/m². In the deterministic results, a single technology dominates each emission bracket. For the SFH case, ASHPs dominate the 5-10 kgCO₂/m² and biomass boilers the <5 kgCO₂/m² bracket. For the MFH case, ASHPs dominate both brackets. This single-technology-dominance aspect is not observed in the stochastic results. The stochastic results for both the SFH and the MFH case exhibit a more balanced allocation of system capacities and all low-carbon technologies are shown to have an important share of the total system capacity. As a result, in both building categories, biomass boilers, ASHPs and even GSHPs are installed with the latter technology being almost absent in the low CO₂ brackets of the deterministic results.

Figure 17. Comparison of optimal energy system solutions of the deterministic and the stochastic models for SFH and MFH building categories. The energy system solutions are grouped in emission brackets according to the CO₂ emissions that they achieve and they are reported in terms of the share of each technology's capacity out of the total capacity of energy system for all solutions in each emission bracket.

Thus, the main conclusion that can be drawn regarding the energy system side of the building retrofits for the SFH and MFH categories is that a diversification of the energy technologies for the buildings is necessary rather than the reliance on a single technology in order to achieve the desired CO₂ levels for the Swiss buildings.

As a final set of results, Table 8 presents the most typical solutions of the stochastic analysis that lie within the 10±2 kgCO₂/m² target range for both the SFH and MFH building categories. A wide range of solutions regarding the envelope retrofit is observed ranging from No retrofit to Full retrofit. Regarding the energy systems, a dominance of ASHP and GSHP technologies is observed in this case, while biomass-based solutions are less frequent. Finally, given the possible cost reductions assumed in the robust model for both PV and battery technologies, all solutions include PV panels, while the majority also includes battery storage systems.

Table 8 Most typical building retrofit solutions that achieve emission levels lower than 10 kgCO₂/m² as an output of the stochastic analysis.

Stochastic Solutions				
MFH				
Envelope retrofit type	Heating system	Solar system	Battery	Share
Window-Wall	ASHP	PV	✗	12.8%
Window-Wall	GSHP	PV	✓	9.5%
Window-Wall	ASHP	PV	✓	6.8%
No retrofit	GSHP	PV	✓	6.3%
Full retrofit	ASHP	PV	✗	5.4%
Window-Wall	GSHP	PV	✗	5.3%
Full retrofit	GSHP	PV	✓	5.2%
Window	Biomass	PV	✓	4.0%
				55.3%
SFH				
Envelope retrofit type	Heating system	Solar system	Battery	Share
Window-Wall	GSHP	PV	✓	14.6%
Window-Wall	ASHP	PV	✗	8.4%
Full retrofit	GSHP	PV	✓	6.9%
Window-Wall	ASHP	PV	✓	5.6%
Roof	ASHP	PV	✗	5.5%
Roof	GSHP	PV	✓	5.2%
No retrofit	ASHP	PV	✗	5.0%
Window	Biomass	PV	✓	4.0%
No retrofit	GSHP	PV	✓	4.0%
				59.2%

3.2. District level solutions

For the 12 typical archetype districts, the multi-criteria optimization for costs and emissions of the energy system is performed. The goal is to identify the kind of district for which building level or district level solutions are optimal. Results are computed again in form of 10 Pareto optimal solutions, calculated using the epsilon-constraint method, from cost to CO₂ emissions optimal. This is done for both different retrofitting scenarios, BAU and NEP as described in Section 2.3. Figure 18 shows the resulting Pareto fronts for the 3 different categories: rural, sub-urban and urban for the BAU 2035 and NEP 2050 scenarios. Figure 19 shows the installed system capacities for the 10 Pareto optimal solutions depending on the CO₂ emission value for the NEP 2050 scenario (BAU 2035 is found in the Figure A8 in the Appendix). As expected, results show that district heating systems are mainly selected for urban and some suburban

clusters, whereas in rural areas individual building systems are preferred due to the district heating restrictions in these cases. Cost optimal solutions often rely on oil-based heating systems, which are gradually replaced by heat pumps (both ASHP and GSHP), waste heat or biomass boilers or combined heat and power plants (CHP) due more stringent CO₂ targets. CO₂ optimized cases require a mix of different energy sources including waste heat, heat pumps or biomass. Results further suggest that, from the overall system capacities installed, around 50 to 80% pertain to a district level system in urban case studies, up to 50% for some denser or industrialized suburban case studies, and building level solutions for rural case studies. PV is deployed to the maximum available capacity for all solutions. Results also show that district level solutions applied in urban neighbourhoods have, in general lower, CO₂ emissions compared to single building solutions in rural neighbourhoods. This is partially due to the higher renewable potential at the district level (waste, manure, and wood), but also due to the lower embodied emissions associated with district level systems.

While the relative selection of district level or building level energy systems remains the same for the different energy scenarios, the actual installed capacities are reduced for BAU 2035 and 2050 scenarios, and further down for NEP 2035 and 2050 scenarios according to the rate presented in Table A5 and A6. This is due to the predicted lower total energy demand due to retrofits in the future. Overall CO₂ emissions can be reduced from BAU 2035 to NEP 2050 retrofitting scenarios by around 10% per Pareto front globally, when mostly building level systems are installed (generally for rural and some of the suburban cases) and only 5% when network solutions are selected (mostly for urban and some of suburban cases where district heating network solutions are retained).

Those results can be explained due to the benefits enabled by district level solutions at urban scale. These district solutions allow for maximization of energy efficiency and minimization of emissions globally compared with building level solutions.

Figure 20 shows the distribution of costs for the NEP 2050 scenario. Resulting embodied CO₂ emissions are shown in Figure 21, respectively. This Figure shows that the overall costs are, in general, increased by 20 to 30% when applying the NEP 2050 scenario retrofitting measures due to their high costs in comparison to the installation of district level solutions, while allowing only a small further decrease of the CO₂ emissions.

When district scale solutions are partially or fully deployed, and retrofitting measures are costly. This is observed in the urban district Grenchen and suburban district Beringen in the NEP 2050 scenario, where costs nearly increased by 50%, while emissions are only reduced by around 10%. For rural cases, the high share of relatively old buildings (<1980) and a high potential for renewable energy (biomass), retrofitting measures present both an economical (costs reduced by 10%) and environmental benefit (emissions reduced by 20%). This is the case for the rural archetype Endingen.

In Figure 20 and Figure 21, it is observed that the retrofit costs and embodied emissions for the districts with a high percentage of new buildings (i.e., Basel), are much lower. Older buildings require more extreme and costly retrofits (e.g., window-wall and full retrofits) in order to achieve targets (<10 kg CO₂/m²), whereas newer buildings could manage to meet the targets with a less expensive roof or window retrofit. It then follows that the retrofit costs for districts with a very old building stocks will be more expensive than retrofits for a new building stock and vice versa. While retrofitting of the building

envelope can cause often significant cost increase, it also enables the reduction of the overall energy consumption and CO₂ emissions. The largest share of life cycle emissions, in all scenarios, currently results from system operation, which is gradually reduced with a shift away from fossil fuels due to more stringent CO₂ emission targets. Embodied emissions for systems and retrofitting show only a small share of overall emissions. Even for the NEP 2050 scenario it contributes only up to 20% of the total emissions.

Figure 18 Pareto front solutions for archetypal districts with BAU 2035 retrofitting (rural, sub-urban and urban archetypes) represented by a dot in light colour scheme; and for district with NEP 2050 retrofitting included, represented by triangles in dark colour scheme.

Figure 19 Optimal energy system selections for archetypical districts for the new energy policy scenario in 2050 (rural, sub-urban and urban archetypes).[1]

Figure 20 Costs distribution for optimal Pareto front solutions for archetypical districts for the NEP 2050 scenario (rural, sub-urban and urban archetypes).

Figure 21 Embodied emissions (EE) for optimal Pareto front solutions for archetypical districts for the NEP 2050 scenario (rural, suburban and urban archetypes).

4. Conclusions

In this work, a framework is presented which can be used to identify an optimal set of building and district measures for a large building data set. The approach is based on a simulation and optimization framework, which uses a multi-criteria decision analysis based on total costs and total life-cycle CO₂ emissions to identify the optimal solutions for the building stock. Furthermore, clustering analyses of Swiss buildings and districts are presented which allows for representation of the heterogeneity of the building stock based on a set of building characteristics, renewable potentials, and regional differences. The developed methodology can be used to assess the effectiveness of energy efficiency measures to reach emission reduction targets, but also allows for the upscaling solutions to the overall building stock of regions or countries to identify their potential impact.

The clustering analysis is applied to the residential and non-residential building stock of Switzerland, which resulted in 50 archetypes for SFH and MFH, and 45 non-residential archetypes pertaining to restaurants, schools, hospitals, offices and shops. Additionally 12 different typical districts could be identified for the categories of urban, sub-urban and rural communities. The archetype buildings and districts are used to identify the cost and CO₂ optimum retrofitting solutions for the Swiss building stock. Additionally, a sensitivity analysis is performed which shows how optimal solutions can change if assumptions pertaining to costs, efficiencies, etc. are changing over time or are not accurately predicted.

Results at building level show that measures which reach emission targets pertain to roof retrofitting, window replacement, and combined window-façade insulation (for older buildings) together with PV installation for nearly all buildings considered. In terms of heating systems, biomass or heat pumps (either GSHP or ASHP) seems to be the most favourable option for single-family houses while ASHPs can also be attractive, particularly for multi-family houses. Results further suggest that a change from a fossil fuel based heating system is required for almost all buildings in order to reach climate targets of Switzerland. These typical solutions (Table 7) cover 68% of all solutions that meet the energy strategy targets in the building level analysis.

The same model and assumptions were used for the robustness analysis of identified solutions. However, in this analysis model parameters including building energy demands, solar radiation patterns, energy carrier prices, emission factors, investment costs, embodied emissions and technical characteristics were treated as uncertain. Results of this analysis show similar patterns, however, in the stochastic case a more balanced allocation of solutions is observed. This includes envelope interventions, as well as system selections. In terms of building envelope interventions, the analysis shows that full retrofitting becomes increasingly important, together with window replacement and façade insulation. On the system side, results show that the high deployment of biomass boilers is reduced and optimal solutions are more evenly distributed between biomass boilers, ASHP and GSHP. Thus, the main conclusion that can be drawn is that diversification of the energy technologies for the buildings is necessary in order to achieve the desired CO₂ levels for Swiss buildings.

The analysis of district archetypes shows that district system solutions are mainly applicable to urban communities and for some suburban areas, whereas building level solutions are clearly the optimal solution for rural areas. In addition, many of the resulting CO₂ emissions were able to reach much lower

values in the urban and suburban case studies than on the building level due to economies of scale. Results for the different urban archetype districts show further that optimal energy system solutions pertain up to share of 50-80% of district energy systems. While the relative selection of district level or building level energy systems remains the same for the different energy scenarios, the actual installed capacities are reduced for BAU 2035 and 2050 scenarios, and further for NEP 2035 and 2050 scenarios.

By applying the typical solutions to the overall building stock of Switzerland, emissions could potentially be reduced by up to approximately 60-80% depending on building type. These results show that the Swiss residential building sector has enormous potential for improvement in terms of sustainability.

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6. Appendix

6.1. Building level assumptions

Figure A1 Building age and heating energy carrier of the 50 SFH and 50 MFH building archetypes

Table A1: Deterministic optimization energy carrier costs and emissions factor assumptions with sources

Energy Carrier	Energy Cost (CHF/kWh)	Life-cycle emission factor (kg CO ₂ -eq)	Source
Electricity	0.237	0.121	[47]; [48]
Feed-in tariff	0.12	0	[49]
Natural gas	0.120	0.228	[50]; [44]
Heating oil	0.101	0.301	[51]; [44]
Wood chips	0.125	0.027	[52]; [44]
Waste	0.125	0.027	[38]; [44]

Table A2: Deterministic optimization's technology capital costs, embodied emissions, efficiencies, and lifetimes with sources

	Capital Costs	Embodied emissions	Efficiency		Source
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Technologies per Function Unit (FU)	Fixed (CHF)	Linear (CHF/FU)	Fixed (kg CO ₂ - eq)	Linear (kg CO ₂ - eq)		Life- time (years)	
Building level							
Oil boiler (kW)	26,600	570	0	51	Old: 0.8 New: 0.85	25	[53] ;[44]
Gas boiler (kW)	27,600	620	0	51	Old: 0.8 New: 0.85	25	[53] ;[44]
Biomass boiler (kW)	27,800	860	0	51	Old: 0.75 New: 0.8	25	[53] ;[44]
Electric boiler (kW)	-	-	-	-	Old: 0.95	-	[53] ;[44]
ASHP (kW)	18,300	1,020	2,329	75	Old: 2 New: 3	15	[53] ;[44]
GSHP (kW)	20,000	2,380	1,806	72	Old: 2 New: 4	20	[53] ;[44]
Gas CHP (kW)	5,000	900	3,750	100	Heat: 0.65 Elec: 0.2	11	[53] ;[44]
PV (m ²)	900	400	0	254	15%	25	[53] ;[44]
ST (m ²)	4,000	1,000	0	184	45%	20	[53] ;[44]
Battery (kWh)	2,000	600	0	157	0.92 (0.1%/hr)	11	[53] ;[44]
Thermal storage (kWh)	1,685	12.5	31	4.7	0.81 (1%/hr)	20	[53] ;[44]
District Level							
Oil boiler (kW)	68,420	130	0	51	0.9	25	[53] ;[44]
Gas boiler (kW)	66,100	200	0	51	0.9	25	[53] ;[44]
Biomass boiler (kW)	146,607	407	0	51	0.85	25	[53] ;[44]
Waste boiler (kW)	66,097	167	0	51	0.85	25	[53] ;[44]
ASHP (kW)	87,840	770	2,329	75	3	15	[53] ;[44]
GSHP (kW)	94,120	1,670	1,806	72	4	20	[53] ;[44]

Biomass CHP (kW)	299	785	0	51	Heat: 0.55 Elec: 0.35	20	[53] ;[44]
Waste CHP (kW)	299	785	0	51	Heat: 0.55 Elec: 0.33	20	[53] ;[44]

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Table A3: Costs and embodied emissions of different retrofits by component and by age with sources

Construction age	Retrofitted component	Retrofit Costs (CHF/m ²)	Retrofit Embodied Emissions (kg CO ₂ – eq/m ²)	Source
≤1918	Façade	290	15.5	[53]; [44]
	Roof	150	13.6	[53]; [44]
	Ground	100	8.80	[53]; [44]
1919-1948	Façade	270	15.5	[53]; [44]
	Roof	150	14.6	[53]; [44]
	Ground	100	8.80	[53]; [44]
1949-1978	Façade	270	15.5	[53]; [44]
	Roof	150	39.9	[53]; [44]
	Ground	100	8.80	[53]; [44]
1979-1994	Façade	240	13.3	[53]; [44]
	Roof	134	35.5	[53]; [44]
	Ground	90	7.91	[53]; [44]
1995-2001	Façade	220	7.92	[53]; [44]
	Roof	123	31.2	[53]; [44]
	Ground	27	2.26	[53]; [44]
2002-2006	Façade	226	9.05	[53]; [44]
	Roof	134	35.6	[53]; [44]
	Ground	53	9.04	[53]; [44]
2007-2009	Façade	223	26.4	[53]; [44]
	Roof	150	32.4	[53]; [44]
	Ground	53	6.78	[53]; [44]
All ages	Windows	850	32.2	[53]; [44]

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751 **6.2. Robustness Assumptions**752 *Table A4: Uncertain model parameters and their probability distributions considered for the robustness analysis*

Uncertain parameters	Probability distribution	Source
Building energy demands		
SFH heat demands	Normal distribution, $N(0.923, 0.120)$ x Nominal heat demand	[54]
SFH electricity demands	Normal distribution, $N(0.937, 0.077)$ x Nominal electricity demand	[54]
MFH heat demands	Normal distribution, $N(0.935, 0.097)$ x Nominal heat demand	[54]
MFH electricity demands	Normal distribution, $N(0.925, 0.047)$ x Nominal electricity demand	[54]
Renewable energy availability		
Solar radiation patterns	Normal distribution, $N(1.072, 0.0674)$ x Nominal solar radiation profile	[54]
Energy carrier prices		
Electricity price	Uniform distribution, $U(0.189, 0.275)$ CHF/kWh	[1]; [54]
Biomass price	Uniform distribution, $U(0.087, 0.149)$ CHF/kWh	[1]; [54]
Gas price	Uniform distribution, $U(0.075, 0.159)$ CHF/kWh	[1]; [54]
Oil price	Uniform distribution, $U(0.062, 0.134)$ CHF/kWh	[1]; [54]
District heating price	Uniform distribution, $U(0.099, 0.145)$ CHF/kWh	[1]; [54]
Feed-in tariff	Uniform distribution, $U(0.084, 0.156)$ CHF/kWh	[1]; [54]
Energy carrier emission factors		

Electricity emission factor	Uniform distribution, $U(110.30, 251.84)$ gCO ₂ /kWh	[1]; [54]
Biomass emission factor	Uniform distribution, $U(-20\%, 20\%) \times$ Nominal value	Own estimates
District heating emission factor	Uniform distribution, $U(-20\%, 20\%) \times$ Nominal value	Own estimates
Gas emission factor	Uniform distribution, $U(-5\%, 5\%) \times$ Nominal value	Own estimates
Oil emission factor	Uniform distribution, $U(-5\%, 5\%) \times$ Nominal value	Own estimates
Investment costs		
Investment cost for PV, batteries	Beta distribution, $B(8, 2.2, 0.1, 1.1) \times$ Nominal cost	Own estimates
Investment cost for ASHP, GSHP, CHP, ST panels	Beta distribution, $B(18, 4, 0.12, 1.12) \times$ Nominal cost	Own estimates
Investment cost for Gas, Oil and Biomass boilers, Thermal storage tanks	Normal distribution $N(1, 0.03) \times$ Nominal cost	Own estimates
Investment cost for retrofit interventions	Beta distribution, $B(18, 4, 0.18, 1.18) \times$ Nominal cost	Own estimates
Embodied emissions		
Embodied emissions for PV, batteries	Beta distribution, $B(8, 2.2, 0.1, 1.1) \times$ Nominal embodied emissions	Own estimates
Embodied emissions for ASHP, GSHP, CHP, ST panels	Beta distribution, $B(18, 4, 0.12, 1.12) \times$ Nominal embodied emissions	Own estimates
Embodied emissions for Gas, Oil and Biomass boilers, Thermal storage tanks	Normal distribution $N(1, 0.03) \times$ Nominal embodied emissions	Own estimates

Embodied emissions for retrofit interventions	Beta distribution, $B(18, 4, 0.18, 1.18)$ x Nominal embodied emissions	Own estimates
Technical characteristics of technologies		
Efficiency of PV	Beta distribution, $B(2.2, 8, 0.8, 1.8)$ x Nominal efficiency	Own estimates
Efficiency of ASHP, GSHP, CHP, ST panels	Beta distribution, $B(4, 18, 0.82, 1.82)$ x Nominal efficiency	Own estimates
Efficiency of Gas, Oil and Biomass boilers	Normal distribution $N(1, 0.03)$ x Nominal efficiency	Own estimates

6.3. District level assumptions

Table A5: Retrofitting rates per building age category for BAU and NEP scenarios (according to Prognos 2012).

Construction period	SFH 2035		SFH 2050		MFH 2035		MFH 2050	
	BAU	NEP	BAU	NEP	BAU	NEP	BAU	NEP
≤1918	0.19	0.36	0.265	0.57	0.285	0.385	0.445	0.59
1919-1948	0.184	0.354	0.299	0.558	0.245	0.389	0.385	0.598
1949-1978	0.184	0.354	0.299	0.558	0.245	0.389	0.385	0.598
1979-1994	0.09	0.223	0.176	0.506	0.162	0.299	0.32	0.613
1995-2001	0.09	0.223	0.176	0.506	0.162	0.299	0.32	0.613
2002-2006	0.09	0.223	0.176	0.506	0.162	0.299	0.32	0.613
2007-2009	0.09	0.223	0.176	0.506	0.162	0.299	0.32	0.613
2010-2014	0.09	0.223	0.176	0.506	0.162	0.299	0.32	0.613
>2014	0.09	0.223	0.176	0.506	0.162	0.299	0.32	0.613

Table A6 Share of selected optimal retrofitting interventions per age category

Construction period	Roof		Ground		Wall		Window		Window-Wall		Full	
	SFH	MFH	SFH	MFH	SFH	MFH	SFH	MFH	SFH	MFH	SFH	MFH
≤1918	0.75	0.56	0	0	0	0	0	0.25	0	0.13	0.25	0.063
1919-1980	0.589	0.20	0	0	0.012	0	0.092	0.37	0.214	0.41	0.093	0.014
>1980	0.442	0.61	0	0	0.12	0	0.299	0.26	0.14	0.13	0	0

Figure A2 Histogram showing the distribution of raster cell density in Figure 4. Cells below 2,800 m²/km² were classified as rural, cells between 2,800 m²/km² and 16,000 m²/km² were suburban, and cells above 16,000 m²/km² were urban

District level system assumptions

Figure A3 Energy demand after aggregation is calculated per typical district (e.g. Basel)

Year 2018 (hourly)

6.4. Building level results

Non-Residential Building Solutions

In **Error! Reference source not found.**, the residential building level decisions are shown. Figure A.1 and A.2 show the corresponding solutions including non-residential buildings for retrofits and systems respectively.

Figure A4 Distribution of the non-residential building solutions for retrofits. Solutions are groups by CO₂ emissions

Figure A5 Distribution of the non-residential building solutions for the system selection. Results are categorized by CO₂ emissions

Figure A shows the breakdown of the objectives (both cost and emissions)

Figure A6 Breakdown of emissions and cost by type (i.e., conversion technologies, storage technologies, retrofits, operation, etc.)

6.5. District level results

District level Pareto front per scenario – BAU, NEP

Figure A7 Pareto front (Urban – Suburban – Rural) for the BAU 2035 scenario

CO₂-minimisation (kgCO₂/m²) – BAU 2035

Figure A8 Optimal energy system selections for archetypical districts without retrofitting (rural, suburban and urban archetypes).

Figure A9. Embodied emissions for optimal Pareto front solutions for archetypical districts for the BAU 2035 scenario (rural, sub-urban and urban archetypes).

Figure A2 Costs distribution for optimal Pareto front solutions for archetypical districts for the BAU 2035 scenario (rural, sub-urban and urban archetypes).

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