Case study 2023-2024

Literature Review

Matching residential cooling demand with rooftop PV

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1 Introduction

With rising temperatures resulting from climate change, the electricity demand for air conditioning systems and other cooling technologies is increasing across Europe. Currently, cooling systems in buildings can represent as much as 50 % of peak electricity demand during extremely hot days, and the global electricity usage for cooling in 2012 was 2200 TWh, or 18.5 % of annual electricity consumption in buildings [1]. The cooling demand is highest during the hottest hours of the day when solar irradiance, and therefore photovoltaic (PV) electrical generation, conveniently also reaches its peak. In addition, temperature correlates with PV generation geographically, making PV a promising energy source to match rising cooling demands[1], [2].

Understanding the relationship between PV and cooling has important implications for further grid integration of PV systems, decarbonization of the energy sector, and renewable energy policies. Quantifying the ability of diurnal solar energy production to match cooling demand loads can help energy companies understand the scale of solar modules needed to meet cooling demand, or if other technologies such as thermal or battery storage might be required.

Several studies examining the synergy between electric cooling demand and PV generation, using various modelling approaches have been published. Drawing on these previous models and weather data, this study will utilize a physical model of four residential building types to estimate cooling demand in Switzerland. The calculated demand will be compared to a simulation of hourly rooftop PV generation. By varying simulation parameters, the model will be made operational all over the European Network of Transmission System Operators for Electricity (ENSTO-E) region.

Here, we conduct a literature review of research previously done on the topic of correlating PV generation to building cooling demand. We investigate current and best practices for developing models that output hourly solar energy production and cooling electricity demand based on solar irradiance and temperature data. We also assess data that can be used to specifically model different types of residential buildings in Switzerland and in the ENSTO-E operating region. The findings of this literature review will then be considered when implementing our own model and analysis.

1.1 Existing Cooling by PV Models

There are currently models that determine the ability of PV generation to match cooling demand, such as the one developed by S. Laine et. al [1]. The aim of their model was to globally quantify the synergy of PV and cooling. The researchers in this study built a model where they selected a square grid inside each region, and used NASA MERRA-2 weather data [3] to produce a plot of the daily temperature. This was used to model the electricity required for cooling for the entire population of different countries, taking into account the proportion of houses with cooling systems (estimated using GDP), energy efficiency of the buildings, etc. The researchers also used a software tool to model the size of a PV array needed to match the averaged yearly cooling demand in the region, and then plotted the hourly output of this array given solar irradiance and weather data, as seen in Figure 1. The researchers compared the two plots, showing that the PV system can meet 55.5% of the cooling electricity demand on an hourly basis [1]. They found that temperature (cooling demand) lags behind PV generation, leading to overproduction during noon hours and underproduction during evening hours due to the thermal dynamics of the building. It was also found that adding a 1 m^3 water-based latent thermal storage to every household could increase the fraction of cooling demand met with PV from 55% to 70% [1].

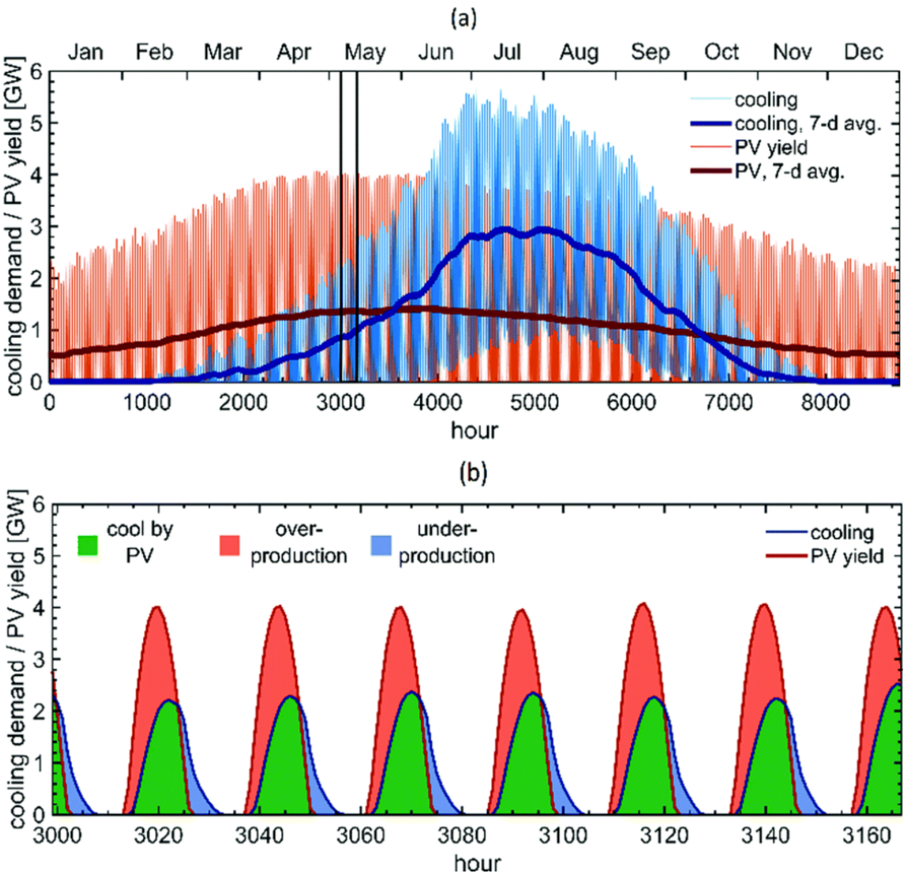

Figure 1: Output of Existing Model Showing relationship between hourly PV production and cooling demand for a region [1]

Other research, conducted by Kan et. al in 2022, investigated how an increased cooling demand may make large-scale investments in PV more cost effective. Using a top-down modelling approach to estimate total cooling demand as a percentage of total electrical demand in various regions, the researchers used an economic analysis to determine if using PV generation was the least expensive method to generate the energy needed for cooling for each hourly data point. They found that electric cooling can be powered at a cost up to 50% lower than the cost for remaining electricity demand if paired with an appropriately-sized PV system [4]. The implications of this study are to show investors and policy makers that powering cooling with PV systems is both economically and environmentally viable.

The model developed here will vary from previous studies by approaching the cooling demand calculation differently. Additionally, it will project electrical power consumption for residential cooling until 2050, taking into account rising temperatures and increased adoption of space cooling systems with increasing efficiencies. The findings will then be corroborated with the results of existing models using similar methodologies to ensure consistent results.

2 Cooling Demand Model

Our model consists of two key sub-models: the PV generation model and the cooling demand model. This section focuses on the latter, providing a brief summary of prevalent techniques in the literature and insights into the current landscape, followed by a comprehensive description of the physical model of household thermodynamics. Additionally, a preliminary framework for the construction of our model is presented here.

Cooling demand modelling is an essential aspect of energy demand and supply planning, which

seeks to comprehend and forecast the power prerequisites for cooling systems in diverse contexts. Physical models can significantly assist in optimising energy-efficient cooling technologies and networks, thereby supporting sustainable urban development and climate resilience.
Existing models can be classified into two primary types: bottom-up and top-down methods. Top-down models evaluate cooling demand on a broader scale, often incorporating the typical attributes of the housing sector. Whereas bottom-up models start at the individual building level and take into account house-specific parameters. As a result, they have higher resolution but are more difficult to up-scale. Bottom-up models are analyzed here, as this is the method we will implement in our case study. An overview of both bottom-up as well as top-down cooling demand models can be found in Frayssinet et al. [5].
Bottom-up models typically require two primary data sources: the physical characteristics of the building and the behavioural data of its occupants. Subbiah et al. [6] developed one such model, in which they estimate the demand for residential energy by analysing corresponding factors such as household activities, occupancy patterns and physical properties. In addition to replicating the electricity demand resulting from appliance usage, the crucial feature of their initial approach is the integration of a space heating and cooling demand model. The computation takes into account climate, housing unit dimensions, and the type of cooling technology. Emphasis is placed on the physical aspects of residential properties, such as wall area, floor area, wall type, and insulation. Fourier's law is employed to calculate the entirety of energy consumption.
Muratori et al. [7] created a bottom-up model that calculates the total electricity demand of a given household with a time resolution of 10 minutes. However, the energy required to maintain the desired temperature inside the dwelling is generated on a second-by-second time grid. To calculate the cooling energy consumption, they take into account the thermodynamic evolution of the air. This considers the temperatures inside and outside the house, the air mass flow rate, the specific heat, and the thermal resistance of the house. They validate their model in two steps. First, they compare their results with the measured consumption of the state used to calibrate the model. Secondly, their simulation is used to model the energy consumption in a second state, which is not considered in the parameter configuration.
Another comparable approach is presented in Shao, Pipattanasomporn and Rahman [8]. They developed appliance-level load models for space cooling, space heating, clothes dryers, and electric vehicles. The cooling demand model considers the building structure, number of residents, outdoor temperature, cooling capacity, and power consumption of the cooling units. The physical model incorporates the heat resistance of the floor, ceiling, and windows. Occupancy of the residents is only taken into account through uniform random functions that set temperature points. The validation of the model involves collating the demand measured during various runs of the model with different parameters and subsequently comparing it with measurement data.
While Shao, Pipattanasomporn and Rahman [8] and Subbiah et al. [6] developed load models that can generate intra-day load profiles with high resolution, the model implemented by Ghedamsi et al. [9] calculates the Algerian cooling demand bottom-up with annual resolution for different household types. This method assumes that there is a proportional relationship between the energy demand for cooling and the difference between the base temperature and mean outdoor air temperature. To calculate the annual cooling energy demand, the degree-days method is used. In addition to this, other factors are taken into account, such as the heat transfer coefficients of the walls and the coefficient of performance of various cooling technologies. The model is utilised to project cooling requirements for Algerian residential dwellings up to 2040.

2.1 Building Energy Model Parameters

This subsection presents a summary of common approaches to the physical modelling of thermodynamics in households, and the resultant cooling demand. Furthermore, it provides an overview of the parameters to consider when modelling electrical cooling demand.
The simple approach adopted by Subbiah et al. [6] uses Fourier's law to calculate the electrical demand for cooling. The equation is expressed as:

$$Q = \frac{S \cdot (T_{\text{inside}} - T_{\text{outside}})}{R}, \tag{1}$$

where T_{inside} is the desired indoor temperature, T_{outside} is the current outdoor temperature, S is the total cooled area, and R is the thermal resistance of the household. While this approach can be implemented quickly, it fails to consider the thermal inertia of buildings.
Shao et al. [8] summarized a comprehensive approach that considers the thermal inertia of buildings. Their model for cooling demand consists of several steps. Initially, it is necessary to establish whether cooling is switched on or off in the household. This is measured for each time step i using the variable $w_{AC,i}$. The definition of $w_{AC,i}$ is as follows [8]:

$$w_{AC,i} = \begin{cases} 0, & T_i < T_s - \Delta T, \\ 1, & T_i > T_s + \Delta T, \\ w_{AC,i-1}, & T_s - \Delta T \leq T_i \leq T_s + \Delta T. \end{cases} \tag{2}$$

Here, T_i represents the present temperature of the room, T_s denotes the desired temperature set by the thermostat, and ΔT signifies the permissible temperature deviation.[1] Subsequently, the temperature evolution is modelled. The temperature T_i at each time step is determined as follows [8]:

$$T_{i+1} = T_i + \Delta t \frac{G_i}{\Delta c} + \Delta t \frac{C_{HVAC}}{\Delta c} w_{AC,i}, \tag{3}$$

where Δt is the time step length, G_i is the heat gain rate of the house at time i, C_{HVAC} is the cooling capacity of the installed technology, and Δc is the energy required to change the temperature of the house by one degree. The heat gain rate G_i at each time step can be calculated by [8]:

$$\begin{aligned} G_i = &\left(\frac{A_{\text{wall}}}{R_{\text{wall}}} + \frac{A_{\text{window}}}{R_{\text{window}}} + \frac{A_{\text{ceiling}}}{R_{\text{Ceiling}}} + \frac{11.77\text{BTU}}{\text{°F ft}^3} n_{ac,i} V_{\text{house}} \right) (T_{out,i} - T_i) \\ &+ SHGC \cdot A_{\text{windowsouth}} \cdot H_{\text{solar}} \frac{3.412 \frac{\text{BTU}}{\text{WH}}}{10.76 \frac{\text{ft}^2}{\text{m}^2}} + H_p. \end{aligned} \tag{4}$$

Variables represented by R correspond to thermal resistance, while those represented by A correspond to area. The parameter $n_{ac,i}$ refers to the number of air changes, V_{house} measures the house volume, and $T_{out,i}$ indicates the outdoor temperature. Additionally, $SHGC$ denotes the solar heat gain coefficient of windows, H_{solar} is the solar radiation heat power, and H_p represents the heat gain from people. Finally, the energy needed to increase or decrease the temperature of the house by one degree can be calculated using the equation [8]:

$$\Delta c = C_{\text{air}} \cdot V_{\text{house}}, \tag{5}$$

where C_{air} denotes the specific heat capacity of air which is assumed to remain constant at room temperature. The cooling power demand can now be determined by aggregating $C_{HVAC} \cdot w_{AC,i}$

[1] Note that in the original work, there is an extra component that corresponds to the demand response. It has been left out here because it is irrelevant to our study.

across all time intervals.
The key finding of this review is that cooling demand models require a set of parameters, corresponding to the building construction, household and occupant characteristics, the used cooling technology, and the outdoor climate.

3 Cooling Technologies

After determining the energy needed for space cooling in Europe, its value must be converted into the actual electrical power needed, using the coefficient of performance (COP) of the physical cooling system . The COP, depends on the cooling technology used and is defined in the following equation:

$$COP = \frac{|Q|}{|W|} \tag{6}$$

- Q is the useful heat **supplied or removed**
- $W > 0$ is the **net work** put into the system in one cycle

Presently, a broad variety of cooling technologies are available on the market. While there are several emerging space-cooling alternatives that show promise, they are not yet competitive with the prevalent vapour-compression systems in terms of short and medium-term cost. Before newer cooling technologies such as solar-thermally-driven heat pumps or reversible ground source heat pumps can be adopted on a wide scale, further development is needed to decrease costs and increase their market exposure and competitiveness. Our study will focus on residential buildings and, according to Elnagar et al. [10], 99% of the cooling technologies on the market for residential buildings in Europe are vapour-compression air-conditioning systems, like the one shown in Figure 2 and 3. However, not all systems on the market are vapour-compression cycles. A small quantity is covered by thermally-driven heat pumps, according to Elnagar et al. [10], which we will neglect in our cooling model.

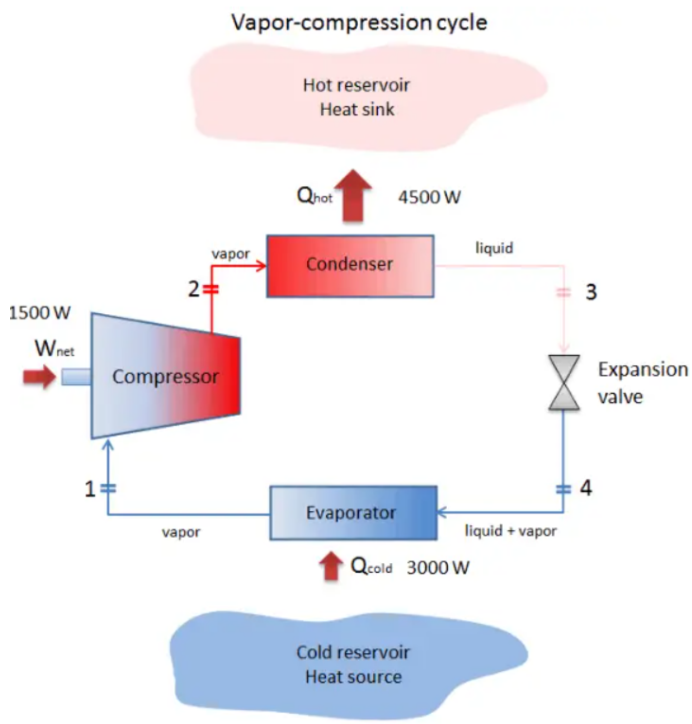

Figure 2: Vapour-Compression Refrigeration cycle

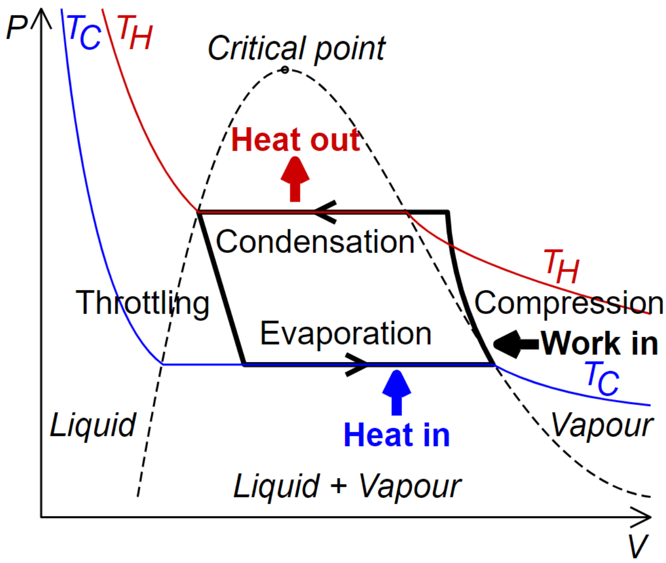

Figure 3: P-V diagram of a vapour-compression cycle

In the past few years, efficiencies of vapour-compression cycles have risen significantly. The average in the year 1992- 1994 was at around 2.80 [11]. In 2007, the average COP had climbed to around 3.60, representing a 28.7% increase in average efficiency over a fifteen-year period. Today there are systems available with ultra-efficient units with a COP of 5.80 [12]. These higher efficiency cooling systems will become more prevalent in the future as new buildings are built, however, we will base our analysis on the vapour-compression systems as they currently dominate.

In this study, an estimated average **COP of 3.5** is used to convert the energy demand into electrical power demand, although there are more efficient products on the market nowadays, because there are also still older technologies being used. This estimation may be changed during the development of the cooling model.

4 Photovoltaic Generation Model

This study seeks to meet the rising cooling demands of residential building through solar power generation using rooftop photovoltaic installations. In the following an overview of the technology and modelling of PV is provided.

4.1 Single Cell Model

Photovoltaic cells generate useful power by means of converting irradiance $\boldsymbol{I_r}$ [W/m^2], which describes the flux of solar radiation incident on a given surface, into an electric current [13]. This happens through the absorption of photons into a semiconductor material with an internal electric field, often a PN-junction, and the subsequent generation of electron-hole pairs [14].

The photovoltaic effect of a single cell can be represented by an equivalent circuit, as seen in Figure 4. The I-V curve, which characterizes the current to voltage relationship at the cell's electrodes, can be modelled using five parameters (I_{ph}, I_0, V_t, R_S, R_P), per [15]:

$$I = I_{ph} - I_D - I_P = I_{ph} - I_0(\exp(\frac{V + IR_s}{V_t}) - 1) - \frac{V + IR_s}{R_p} \tag{7}$$

I_{ph} is the photo current, proportional to the irradiance $\boldsymbol{I_r}$ and is assumed to be constant along the I-V curve. R_p and R_s represent the parallel and series resistance losses in the cell.

The current I_D through the PN-junction is represented by the Shockley diode equation, with saturation current I_0 and diode thermal voltage $V_t = nKT/q$, where n is the diode ideality factor; k is Boltzman's constant ($1.381 \cdot 10^{-23}$ J/K); q is the elementary charge ($1.607 \cdot 10^{-17}$ As) and T is the cell temperature (K). A higher numerical accuracy could be achieved by modelling a second parallel diode, however, as noted by T. Ma et al. [15], these models are computationally sub-optimal because they contain two exponential terms. Conversely, neglecting the resistive effects in the cell leads to unsatisfactory inaccuracy, resulting in the five parameter compromise. These parameters can be determined based on data provided by PV module manufacturers.

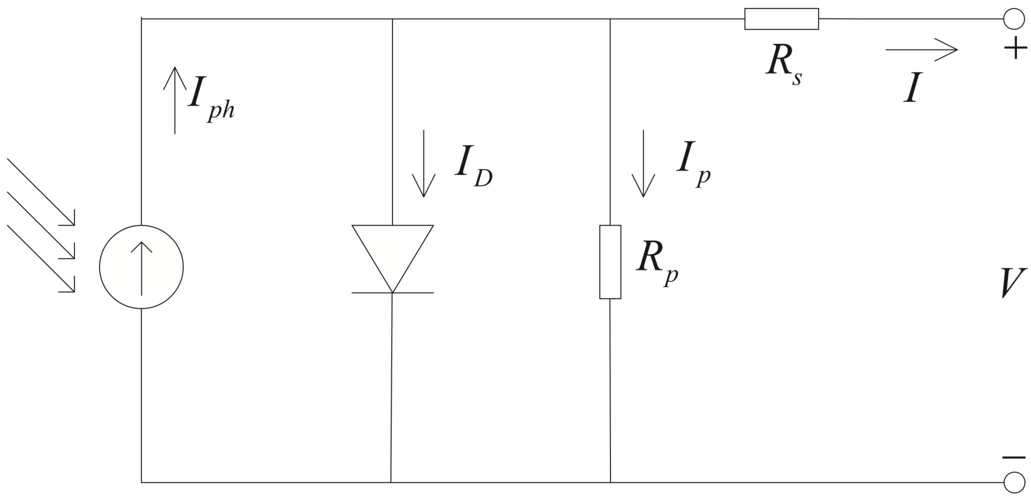

Figure 4: Equivalent circuit of a single PV-cell, taken from [15]

The power P supplied by a PV cell is given by the product of I and V. Therefore, the efficiency η of a cell with an irradiated area A is defined by the ratio of the generated electrical power to the total solar irradiation [13]:

$$\eta = \frac{I \cdot V}{\boldsymbol{I_r} \cdot A} \cdot 100\% = \frac{P}{\boldsymbol{I_r} \cdot A} \cdot 100\% \tag{8}$$

4.2 PV System Model

A PV module is composed of a number of PV cells, connected in series, increasing the total voltage, or in parallel, increasing the total current, and encapsulated on a single panel. These modules are in turn connected serially and in parallel to form an array, which is connected to a battery and charge controller as well as an inverter. The inverter converts the produced direct current (DC) into an alternating current (AC), which can be used for cooling or it can be fed into the grid during periods of overproduction. [13]

In [15], a formula for the I-V characteristic of a PV array of N_P parallel strings of N_S serially connected cells, based on Eq. 7 is provided.

For any given ambient conditions (current irradiance and temperature) there exists an optimal operating point on the I-V curve of the PV system, where the power output P is maximized. This point can be reached by regulating the output voltage V, using a maximum power point (MPP) tracking controller [13].

In addition to the efficiency losses from the photovoltaic effect shown in Eq. 8, the system may incur losses due to heat dissipation within the cells, resistance in the cabling, inverter losses, and imperfect operating point tracking. [13] The inclination of modules is another factor which affects efficiency, as the total irradiation absorbed varies with it. Commonly, the optimal inclination of a module is roughly the latitude angle of the site. However, this is assuming the modules are not mutually shading each other, a complication explored in [16], where the field inclination itself is also taken into account.

As monocrystalline silicon photovoltaics is the most mature commercially-available technology, it will be used as the baseline for this study. According to [17], monocrystalline silicon PV modules vary in their efficiency between 14% and 22%. We will therefore, when necessary, assume an efficiency of $\eta = 20\%$, though this number may be changed later on.

4.3 Simulation Methods

Simulating the behaviour of PV systems can be done in a variety of ways, emphasizing different aspects. In [18], 32 different PV softwares were compared and classified. A development towards algorithms, which take multiple renewable technologies into account, could be observed, as well as the increased importance of artificial intelligence. In [15], different methods to calculate the five parameters needed for the I-V characteristic are enumerated: on the one hand, solutions to the equations can be found analytically, but this requires simplifications and assumptions; on the other hand, there exist iterative numerical methods, but these generally demand too much computation. The authors developed and validated a combined method, with satisfying results.

As mentioned in the previous section, regulating the electrode voltage V to maximize the power output P is essential to running an effective PV system. [13] presents many algorithms developed to achieve this, the most common of which is referred to as "Perturb and Observe", which decreases the voltage based on the last two power output measurements. However, as it oscillates around the MPP, it is not an optimal solution. More sophisticated methods, such as the "Incremental Conductance" technique, take the partial differentials of P with regards to I and V into consideration, increasing both accuracy and computation time. Artificial neural networks represent a novel method to determine the MPP, which also takes the ambient temperature and irradiance into account. In [19], the MPP is determined numerically using the calculated parameters and the characteristic equations. This is highly accurate, however computationally costly.

In summary, it is pertinent to model the PV system accurately to optimize its power output. This requires datasheets from module manufacturers as well as site-specific temperature and irradiance data, such that the necessary parameters may be calculated.

5 Data

Modelling of rooftop-PV systems and cooling demands requires many inputs. The more modelling parameters provided by verified data sets that are used, the more accurate our model will be. Temperature and solar irradiance data, which are crucial for both PV and cooling models, will play an important role. Because we need both current data and future forecasts of temperature, we will acquire it from the Copernicus Climate Data store, which is uniquely suited for our needs.

5.1 Copernicus Climate Data Store

Copernicus is a European observation program which provides free data and measurements via an open-access toolbox. The Climate Data Store (CDS) toolbox offers a wide variety of information such as an annual mean temperature in Europe or climate trends in the upcoming years.

5.2 European Space Cooling Demands

Demand for space cooling up until 2050 in Europe was modelled in the 2016 "Space Cooling Technologies in Europe" report commissioned by the EU [20]. It analysed the cooling demand today across all EU countries and made predictions on the increased demand up to 2050. Their predictions were based on the increase of number of cooling degree days in each country. Figure 5 shows their results for a selection of countries in the European Union.
Cooling degree days (CDD) is a cooling need indicator, which is calculated by looking at the maximum and minimum temperatures for each day i of the year and comparing their average to a reference temperature (here 18°C). It is calculated as follows :

$$CDD = \sum_{i=1}^{\text{days of year}} \max(0, \frac{T_{\text{max, }i} + T_{\text{min, }i}}{2} - T_{\text{ref}}) \tag{9}$$

Cooling Degree Days	2015	2030	2040	2050
Austria	226	280	323	365
Belgium	89	95	97	100
Bulgaria	317	384	434	483
Croatia	325	377	415	453
Cyprus	1417	1467	1498	1529
Czech Republic	117	161	199	237
Denmark	43	74	101	128
Estonia	30	59	84	110
Finland	24	49	72	95
France	236	254	262	270
Germany	118	149	174	200
Greece	889	931	953	974
Hungary	259	320	368	416
Ireland	6	7	7	7
Italy	607	644	662	680
Latvia	42	82	118	154
Lithuania	76	123	163	202
Luxembourg	115	121	122	123
Malta	1258	1321	1361	1401
Netherlands	42	48	52	56

Figure 5: **Cooling degree days across different countries.**

They also surveyed the dominant space cooling technologies as well as the performance and cost data of each of them, shown in Figure 6. They found that residential cooling systems are mostly centered around three technologies: air-cooled chillers ($\leq$ 400 kW), moveable units and split systems. The average installation size of cooling systems are around 85 W/m^2 but can vary a lot by country; Cyprus for instance averages cooling systems requiring 180 W/m^2[20]. Cooling market saturation data from the United States was also taken into account when predicting future cooled surface areas (see Figure 7)). Figure 8 shows the total expected cooling supply up until 2050. The energy consumption is expected to quintuple between 2015 and 2050 [20].

	movable	Split <5kW	Split >5kW	VRF	Chiller air <400kW	Chiller water <400kW
Cyprus	94%	82%	58%	2%	20%	20%
Malta	95%	82%	59%	2%	20%	20%
Greece	95%	82%	58%	2%	20%	20%
Italy	95%	83%	59%	2%	20%	20%
Spain	68%	76%	47%	9%	23%	23%
Romania	91%	72%	38%	8%	33%	35%
Portugal	87%	73%	38%	8%	34%	35%
Croatia	82%	69%	36%	7%	32%	33%
Bulgaria	79%	66%	35%	7%	31%	32%

Figure 6: **Shares of sales in residential sectors in hottest EU countries.**

5.3. Cooled Surface areas

RESIDENTIAL

	2015	2030	2040	2050
Austria	1.4%	2.8%	3.5%	4.4%
Belgium	1.5%	2.7%	2.9%	3.1%
Bulgaria	4.6%	9.6%	12.3%	13.8%
Croatia	6.5%	19.4%	29.1%	35.1%
Cyprus	64.1%	71.2%	73.8%	75.3%
Czech Republic	1.3%	2.8%	6.0%	11.1%
Denmark	0.7%	3.5%	7.2%	10.2%
Estonia	0.4%	2.3%	5.1%	7.5%
Finland	0.3%	0.5%	1.6%	4.0%
France	5.9%	13.1%	23.6%	31.7%
Germany	0.4%	0.7%	0.9%	1.1%
Greece	22.9%	34.0%	48.2%	56.9%
Hungary	2.8%	5.5%	12.9%	22.3%
Ireland	0.3%	0.8%	1.0%	1.2%
Italy	17.8%	27.2%	44.8%	56.3%
Latvia	0.5%	2.8%	6.0%	8.9%
Lithuania	1.0%	5.0%	10.2%	14.7%
Luxembourg	2.0%	7.6%	13.0%	16.8%
Malta	52.9%	64.9%	69.3%	71.7%
Netherlands	0.7%	0.8%	1.0%	1.2%
Poland	0.8%	1.6%	2.5%	3.8%
Portugal	3.8%	6.7%	17.1%	32.7%
Romania	7.5%	13.4%	22.1%	30.9%
Slovakia	2.7%	10.9%	19.7%	26.1%
Slovenia	4.4%	15.1%	24.5%	30.8%
Spain	14.2%	18.9%	34.4%	49.4%
Sweden	0.7%	0.9%	1.1%	1.4%
United Kingdom	0.4%	0.7%	1.3%	2.2%
EU 28	**6.3%**	**10.1%**	**17.5%**	**22.9%**

Figure 7: **Expected cooled surface areas up to 2050.**

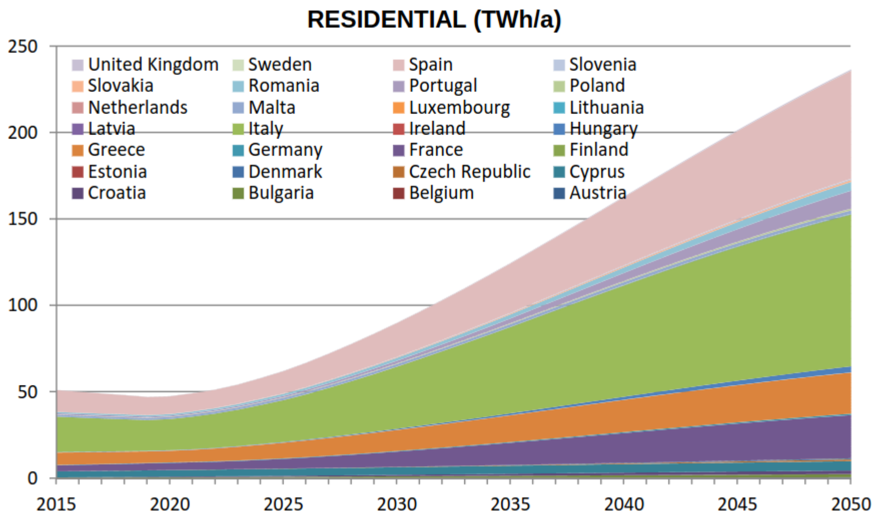

Figure 8: **Total Cooling Supplyin Europe**

5.3 Size of houses

Our cooling model will specifically be geared to residential buildings. While we are hoping to make three distinct categories of dwellings for simplicity, the Swiss Federal Office offers interesting statistics on the size of Swiss houses as well as the average floor size in Switzerland. These data allow us to create dwelling categories for space cooling modelling. For example, data on the number of houses with specific room sizes is available for all of Switzerland (Figure 9). Data on the average size of houses is also available (Figure 10).

Dwellings by number of rooms

	1990	2000	2010	2022
Total dwellings	3,159,977	3,569,181	4,079,060	4,741,917
1 room	237,075	241,239	260,047	305,354
2 rooms	463,941	502,636	559,278	707,619
3 rooms	889,145	976,211	1,077,308	1,283,459
4 rooms	824,230	959,666	1,129,971	1,300,126
5 rooms	419,720	524,787	624,469	705,911
6 rooms and more	325,866	364,642	427,987	439,448

Figure 9: **Number of the dwelling with specific number of rooms.**

Floor space of dwellings

In 2022 the average floor space per dwelling was 99m². The relative stability observed since 2000 (97m²) can be explained by the fact that dwellings built prior to 1981 (60% of the housing stock) have an average floor space of less than 100m². The size of more recent dwellings, however, is larger, and dwellings built between 2001 and 2005 have an average floor space of 131m².

Average floor space of dwellings by period of construction, 2022

Period of construction	Average floor space
Total	99.0m²
before 1919	96.4m²
1919 - 1945	92.2m²
1946 - 1960	83.8m²
1961 - 1970	83.0m²
1971 - 1980	93.1m²
1981 - 1990	106.8m²
1991 - 2000	112.1m²
2001 - 2005	131.1m²
2006 - 2010	124.7m²
2011 - 2015	115.0m²
2016 - 2022	101.9m²

Figure 10: **Floor space of dwellings**

6 Conclusion

Current research shows that there is a strong correlation between residential cooling demand and hourly PV generation, and the demand for cooling will only increase in the decades to come.

Approaches to modelling both cooling and PV can vary, depending on which factors the studies are most interested in. We will implement best practices for modelling PV generation and building cooling demand based on the literature, with an emphasis on capturing the variance in different types of residential buildings, different European countries, and projections into the coming decades. An understanding of the relationship between PV and cooling is pivotal for energy companies like BKW, as they seek to meet the needs of a warming world with decarbonized energy sources.

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