

# **Optimal hybrid energy system architecture for peak shaving - A Stochastic Approach**

Seminar Paper



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## 1 Abstract

Many nations are faced with the challenge of achieving the goals set out in the Paris climate agreement and at the same time securing the supply of energy in the long term. As a result, renewable energies, especially wind and solar, have become increasingly important. The problem with renewable energies, however, is that their production cannot be controlled. This can lead to excesses of energy in the grid and together with the already existing demand peaks, this leads to a higher complexity of the grid balancing, as well as higher costs for the grid operators. To solve this problem, different approaches have been developed. One of these approaches is dynamic pricing, which aims to influence consumer behaviour and thus mitigate peaks. Another approach is the hybrid energy system architecture. In this case, different energy sources and batteries are combined.

In this paper, it will be investigated whether dynamic prices in connection with renewable hybrid energy system architectures can reduce demand peaks and at the same time reduce the energy costs of individual households. For this purpose, different scenarios for the production of wind and solar energy, the demand of households and the price of energy are generated on the basis of real-world data. These scenarios are then used as input for a stochastic optimisation model that optimizes the number of solar panels, batteries and wind turbines. In this case, the model does not act on the entire grid level, but at the level of single new housing developments, making the possibilities for the use of renewable energy sources controllable. Sensitivity analyses were used to compare the impact of various factors, such as the degree of hourly energy smoothing and the presence of battery safety capacities.

The results of the analyses showed that the use of dynamic pricing in connection with a hybrid energy system architecture can reduce peak demand cost-efficiently by up to 82%. At the same time, the costs for individual households decrease significantly compared with households without any usage of renewable energy. Furthermore, the chosen method is scalable, which means that it can be applied with the same efficiency to new housing developments independently of its size.

## 2 Introduction

In order to achieve the goals of the Paris climate agreement, the use of renewable energies is of great importance (Gielen et al., 2019, p. 38). In particular, technologies such as wind and solar power will be strongly expanded (Gielen et al., 2019, p. 44; Lacal Arantegui & Jäger-Waldau, 2018, p. 2469). In addition to the advantages of these technologies, which are based on infinite resources such as wind and sun and do not generate any direct emissions, they also have some disadvantages compared to conventional energy generation technologies. For example, the generation is linked to external, uncontrollable factors, which means that it is not possible at all times to produce and when production cannot be controlled. This uncertainty in production, together with the already existing uncertainty in demand, leads to an over- or under-supply of the grid, which must be compensated by the grid operator by buying or selling energy abroad. This balancing results in considerable costs.

Due to these high costs, the topic has attracted a lot of attention in research. As a result, various methods have been developed to reduce uncertainty in energy production and peaks in consumption. This includes approaches such as optimising the renewable energies mix, the use of batteries, and strategies to influence customer behaviour.

The problem with most of these approaches is that they cannot solve the problem of demand and production peaks on their own. Therefore, the approach of hybrid energy system architectures was developed. In this hybrid systems, different renewable and conventional energy sources as well as batteries can be combined (Luna-Rubio et al., 2012, pp. 1079–1080).

This paper combines dynamic prices with a hybrid energy system architecture to reach demand peak shaving while minimizing costs. This is done on the level of planned new housing developments, to make the possibilities for renewable energy usage controllable. For this purpose, the optimal quantity and composition of renewable energy systems and batteries is determined for different degrees of hourly energy purchase smoothing. In other words, the maximum percentage difference in the amount of energy purchased in successive hours (Appendix A). This smoothing is important because even conventional energy sources need a certain amount of time to adjust their production.

The optimization is achieved through a stochastic model and the use of various generated scenarios based on real-world data. To this end, Chapter 3 first gives an

overview of related literature, before Chapter 4 describes the data, scenario generation and the optimization model. Chapter 5 shows the optimization results. Chapter 6 concludes with a discussion of the findings, the conclusion, and an outlook for further research.

### **3 Literature Review**

There is a broad field of research that deals with demand peak shaving.

One possibility for this is the use of batteries as done by Papadopoulos et al. (2020). In their paper, the impact of batteries on demand peaks was investigated considering different demand patterns. Papadopoulos et al. (2020, p. 14) showed that significant peak shaving could be achieved through the use of batteries, even if the utilization of the batteries was very low on average, which suggests that it is not worthwhile economically. Since no renewable energies were used either, the sole use of batteries is not considered further in this paper.

Another way to reduce demand peaks is to directly influence consumer behavior. As an example of this, Yaw et al. (2017) showed that a shift in the timing of working hours can lead to a significant demand peak shaving. Another concept that is easier to implement is the dynamic pricing. In this concept, the price is positively correlated with the overall demand to give consumers the incentive to carry out energy-consuming activities immediately when there is currently low demand or to postpone them when there is currently high demand (Joskow & Wolfram, 2012, 381-382). As this approach can support the use of batteries by taking advantage of short-term favorable prices, it is also considered in this paper. Equivalently, the sales prices will also be dynamic, but significantly below the purchase price.

Hybrid energy systems are a possible option for production stability and self-sufficiency. These systems make use of the various characteristics of the energy sources to compensate for the weaknesses of one source with the strengths of the other (Luna-Rubio et al., 2012, p. 1079). Despite this property, it is usually necessary to use conventional energy sources or batteries, especially when using solar or wind energy. As solar panels, wind turbines and batteries are coherent in the context of this work, they are used as energy sources.

Many of these presented optimization approaches have been tested at the grid level. The problem here is that the status quo is constantly changing, as the private expansion

of renewable energies cannot be controlled. As a result, continuous evaluation and adjustment of the energy generation mix as well as battery capacity is necessary. One possible solution to this is optimization at the level of energy communities. Within this community, the members share the products of their generation assets or sell them if there is a surplus (Villena et al., 2020, p. 1). In this paper, a planned energy community in the form of a new housing development is considered. Through this, the expansion of renewable energies can be regulated. Furthermore, the problem is easier to handle due to the smaller scale, as no regional weather conditions has to be taken into account. On the other hand, it also contributes to solving the overall problem, as a sufficiently high proportion of such settlements can reduce peak demand.

The following research question was formulated based on the related literature and the decisions made:

*Is it possible to peak shave and be economically efficient at the same time through a combination of dynamic energy pricing and hybrid energy system architectures?*

## **4 Methods**

In this chapter, the optimization strategy is presented. First, in 4.1 the underlying problem is presented with all relevant factors such as uncertainties and constraints. Subsequently, the data used are examined in more detail in 4.2. Next 4.3 explains the procedure for generating the various scenarios. Finally, 4.4 describes the model used in detail.

### **4.1 Problem definition**

In the context of modern projects, urban planners are increasingly faced with the challenge of designing new housing developments that are not only visually appealing and practical, but also as environmentally friendly as possible. In addition to the environmental friendliness using renewable energies, this paper primarily discusses the maintenance of grid balance. To ensure this, the planner is faced with the challenge of developing a hybrid system of renewable energies and batteries that enables the community to reduce demand peaks as good as possible. In principle, there are two ways of doing this: reduction of differences in demand quantity between successive points in time or a withdrawal or release of energy into the grid when the load is high

or low. Since this paper deals with the prevention of peaks on a local base and not with their grid wide degradation, the first method is chosen.

This paper presents this challenge in a simplified way. Among the different types of renewable energy, only wind and solar power are available and no other options such as biogas or hydropower.

#### **4.1.1 Decision Framework**

In this Framework the city planner is the decision maker for the here-and-now decisions. He must make the long-term investment decisions, such as the number of solar panels, wind turbines and battery units, at the beginning of the planning horizon. All are associated with different costs, performance and lifetimes (Appendix. B). In addition, an initial long-term strategy for the use of the batteries must be adopted. This involves the planned capacity reserves, as well as the state of charge at the beginning and end of the day. After the community has been established, the urban planner's task ends, and the community becomes the decision-maker. Then daily decisions regarding the purchase or sale quantity, as well as charging or discharging of batteries have to be made. This are the wait-and-see decisions.

#### **4.1.2 Uncertainty Characterization**

Making the here-and-now decisions, the urban planner encounters various uncertainties that he must take into account. Since the weather changes during the year, there are significant differences in production and consumer demand during the year that must be considered. For the wait-and-see decisions, daily weather and demand fluctuations must be considered. In addition, there are also fluctuations in energy prices may influencing the decision process.

### **4.2 Data**

A lot of different data sources are used for the generation of scenarios. They are divided according to demand, energy prices, solar and wind generation. In the following each dataset will be briefly described.

*Demand Dataset:* The demand Dataset is a free accessible dataset including the hourly energy consumption of 29 households (<http://ampds.org>). These are located in the Metro Vancouver area or on Vancouver Island. The buildings included are of different types, e.g. single or multi-storey buildings, modern and old. The equipment also differs significantly, for example in some buildings many systems, such as the heating or the



fireplace, are electrically operated, while in other buildings these systems are operated with gas. As a result, the average consumption of the individual households also differs significantly. The data are from the years 2012 to 2020, but are not consistently available for every household. Approximately 3 years of contiguous data are available for every household. Since some consumption data were unrealistically high, the data set was removed by all data points that were 3 standard deviations above the mean. Also, only complete years were used for each building.

*Solar Energy Generation Dataset:* This dataset is included in the Demand dataset. It contains hourly simulated electricity generation data from photovoltaic systems in the same area as the buildings investigated. The data covers one year. As they were complete and free of errors, no cleaning was necessary.

*Wind Energy Generation Dataset:* This dataset contains hourly energy generation data from wind turbines in Finland in 2019. The data comes from Fingrid, which is Finland's transmission system operator (<https://www.fingrid.fi/>). Since the data set lacked production data for some hours, only days on which data was available for all hours were used. This cleaning leads to data for 344 days.

*Price Dataset:* The price dataset contains auction prices for electricity on the day-ahead market from 2019. The prices are given hourly and refer to the Germany/Luxenburg area. The data are complete and free of errors and therefore do not require cleaning.

### 4.3 Scenario Generation

*Demand scenarios:* Since the data showed clear monthly and daily patterns, a four-step approach was chosen for the scenario generation. First, the total annual consumption was calculated using a normal distribution for twenty-five years. The mean was determined from the consumption data of the data set and was approximate 8000 kWh. This is higher than the current average value for most European countries, however, this deviation is advantageous, as consumption will increase in the future due to an increasing share of electric vehicles. Subsequently, as the daily pattern is the same in each month (App.C, Fig. 10) and the monthly pattern is the same in each year (App.C, Fig. 9), two multinomial distributions were created for mapping monthly and daily consumption patterns. By chaining these three distributions, 9125 daily demands were generated. To reduce this number, both a K-Means and a K-Medoids algorithm were tested. The K-Means algorithm showed clearer results and produced 3 unique

scenarios, shown in Fig.1. These three scenarios differ primarily in the level of demand. Due to the existence of electric heating systems in some of the buildings in the data set, these curves can be interpreted as winter, summer and transition period.

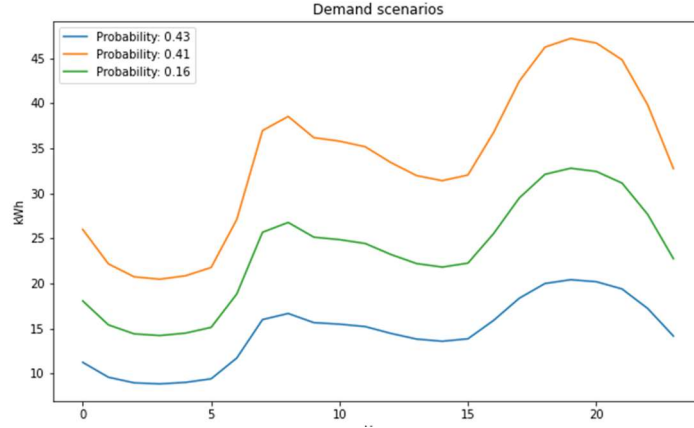


Figure 1 Demand scenarios

*Solar energy production scenarios:* First, the total production quantity and the associated probability were determined for each day. Since the number of solar modules used is to be determined later in the model, the production quantity was scaled to the production of one panel by using a min-max scaler. After scaling the production values they were multiplied by the maximum production (0.4 kWh) of the selected panel and an effectiveness factor (90%). Using the resulting values, a discrete distribution was established, which was used to determine the production of 1000 days. To cover the pattern of production within a day, a multinomial distribution was used. To reduce the scenarios, a K-Means and K-Mediods algorithm was tested and in the end four meaningful scenarios were determined using a K-Mediod algorithm.

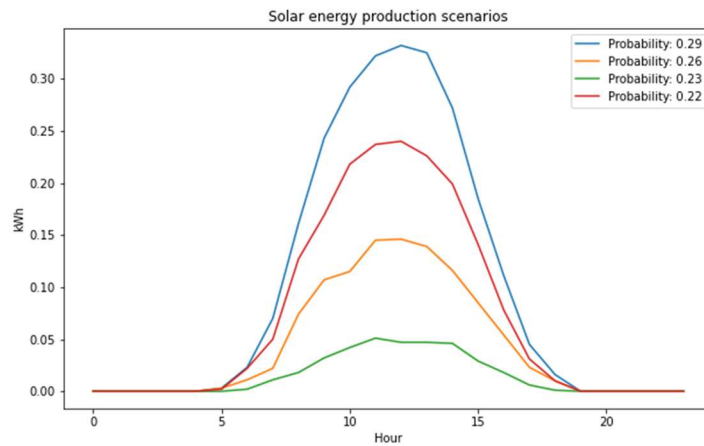


Figure 2 Solar energy production scenarios

*Wind energy production scenarios:* As no specific patterns were discernible in the data on energy generation from wind power, the approach chosen to generate scenarios is comparable simple. Only the real-world data are clustered using a K-Mediod algorithm, resulting in 3 meaningful scenarios, shown in Fig. 3.

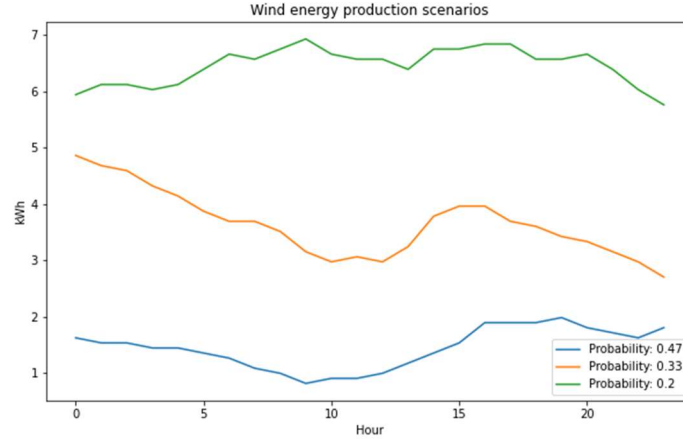


Figure 3 Wind energy production scenarios

*Price scenarios:* For the generation of the price scenarios an approach äquivalent to wind energy generation was used. A K-Mediods was used to reduce the data to four meaningful scenarios, shown in Fig.4.

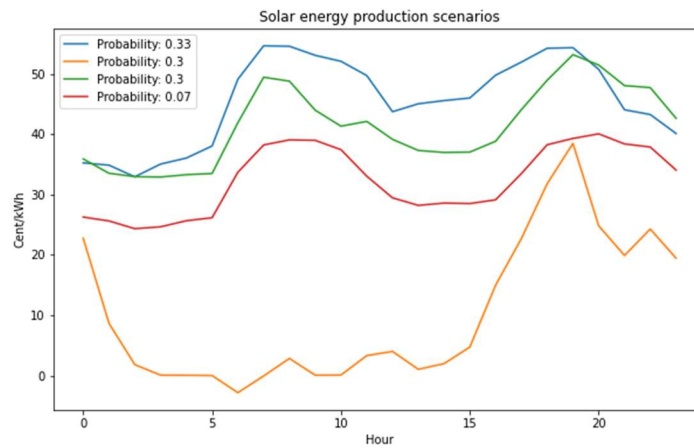


Figure 4 Energy cost scenarios

#### 4.4 Optimization Model

In this chapter, the optimization model used is described. For this purpose, all sets, parameters and variables are first explained in table 1. The objective function used and the constraints are then explained in detail.

Table 1 Sets, Parameters and Variables

	Description
<b>Sets</b>	
$\Omega$	Set with scenarios $\omega \in \Omega$
$T$	Set with hours $t \in [1,24]$
<b>Parameter</b>	
$\Psi$	Maximum permitted percentual change in purchase quantity compared to the previous hour.
$\Theta$	Percentage of the daily production that must be held or kept free in the battery as safety capacity.
$\Lambda$	Selling price = $\Lambda$ * purchase price. Default is 40%
$\Phi$	Percentage of demand that can be eliminated but incurs opportunity costs. Default is 5%.
$\pi_{\omega}$	Probability of each scenario $\omega \in \Omega$ .
$max^S, max^B$	Maximum number of solar panels and batteries allowed per house.
$max^W$	Maximum number of wind turbines allowed.
$max^{Charge}$	Maximum kWh that a battery can store.
$C^S, C^W, C^B$	Fixed costs through the construction of one solar panel, wind turbine, or battery. Calculated for one day.
$C_{\omega,t}^e$	Cost per kWh in scenario $\omega \in \Omega$ during hour $t \in T$ .
$C^{pen}$	Penalty cost per kWh demand reduction.
$num^H$	Number of Houses.
$dem_{\omega,t}$	Demand per house in scenario $\omega \in \Omega$ during hour $t \in T$ .
$prod\_plan_{\omega,t}^S$	Planned production of one solar panel during $t \in T$ in scenario $\omega \in \Omega$ .
$prod\_plan_{\omega,t}^W$	Planned production of one wind turbine during $t \in T$ in scenario $\omega \in \Omega$ .
<b>Variables</b>	
$num^S, num^W, num^B$	Integer; Number of solar panels, wind turbines and batteries purchased; equal in each scenario.

$energy_{\omega,t}^p, energy_{\omega,t}^s$	Float; kWh purchased, sold in scenario $\omega \in \Omega$ during hour $t \in T$ .
$dem\_red_{\omega,t}$	Float; Demand reduction at time $t \in T$ in scenario $\omega \in \Omega$
$SOC_{\omega,t}$	Float; State of charge in kWh in scenario $\omega \in \Omega$ at beginning of hour $t \in T$ .
$SOC_{eod}$	Float; State of charge in kWh at the end of day in each scenario.
$battery_{\omega,t}^c, battery_{\omega,t}^{dc}$	Float; kWh charged, discharged in scenario $\omega \in \Omega$ during hour $t \in T$ .

The variable set shown in (1) will be optimized in the objective function of the model.

$$\boxed{var} = num^S, num^W, num^B, energy_{\omega,t}^p, energy_{\omega,t}^s, dem\_red_{\omega,t} \quad \forall \omega \in \Omega, t \in T \quad (1)$$

The objective function (1) aims to minimise the total costs of all possible scenarios, by minimizing the sum of the fixed investment costs  $C^{Fix}$ , the variable costs  $C_{\omega,t}^{Var}$  and the opportunity costs  $C_{\omega,t}^{Opp}$ .

$$\boxed{Min} \quad C^{Fix} + \sum_{\omega \in \Omega} C_{\omega,t}^{Var} + C_{\omega,t}^{Opp} \quad (2)$$

The fixed investment costs (3) are calculated from the number of solar modules, wind generators and batteries built, multiplied by the respective costs. The costs were computed down to a daily basis.

$$C^{Fix} = num^S * cost^S + num^W * cost^W + num^B * cost^B \quad (3)$$

The variable costs (4) result from the amount of kWh purchased or sold over the course of a day. The probability of the corresponding scenario is included here.

$$C_{\omega,t}^{Var} = \pi_{\omega} \sum_{t \in T} energy_{\omega,t}^p * C_{\omega,t}^p - energy_{\omega,t}^s * C_{\omega,t}^p * \Lambda \quad \forall \omega \in \Omega \quad (4)$$

The opportunity costs (5) result from the amount of kWh that is reduced in all houses over the course of a day multiplied with penalty cost  $C^{pen}$ .

$$C_{\omega,t}^{Opp} = \pi_{\omega} \sum_{t \in T} num^H * dem_{\omega,t} * dem\_red_{\omega,t} * C^{pen} \quad \forall \omega \in \Omega \quad (5)$$

The first two constraints (6) and (7) are very simple ones, limiting the number of solar panels and batteries per house.

$$num^S < max^S * num^H \quad (6)$$

$$num^B < max^B * num^H \quad (7)$$

The next constraint (8) is used to limit the daily amount of kWh that can be sold to the daily production amount. Thus, trade is restricted. It is necessary to avoid artificial demand, in the form of buying and immediately selling energy during optimisation. Without this, (15) and (16) can be bypassed.

$$\sum_{t \in T} energy_{\omega,t}^s \leq \sum_{t \in T} prod_{\omega,t} \quad \forall \omega \in \Omega \quad (8)$$

$$prod_{\omega,t} = prod_{\omega,t}^s + prod_{\omega,t}^w \quad \forall \omega \in \Omega, t \in T \quad (9)$$

$$prod_{\omega,t}^s = num^s * prod_{plan_{\omega,t}}^s \quad \forall \omega \in \Omega, t \in T \quad (10)$$

$$prod_{\omega,t}^w = num^w * prod_{plan_{\omega,t}}^w \quad \forall \omega \in \Omega, t \in T \quad (11)$$

The supply of the required energy is guaranteed by (12). This condition ensures that the sum of solar and wind energy production  $prod_{\omega,t}$ , the trade surplus  $surplus_{\omega,t}^t$  and the battery surplus  $surplus_{\omega,t}^b$  meets the (reduced) demand of all households in each hour  $t \in T$  and scenario  $\omega \in \Omega$ .

$$prod_{\omega,t} + surplus_{\omega,t}^t + surplus_{\omega,t}^b - num^H * dem_{\omega,t} * (1 - dem_{red_{\omega,t}}) = 0 \quad \forall \omega \in \Omega, t \in T \quad (12)$$

The trade surplus (13) is defined as the difference between the purchase and sale of energy in each hour  $t \in T$  and scenario  $\omega \in \Omega$ .

$$surplus_{\omega,t}^t = energy_{\omega,t}^p - energy_{\omega,t}^s \quad \forall \omega \in \Omega, t \in T \quad (13)$$

The battery surplus (14) is defined as the difference between the discharging and charging batteries in each hour  $t \in T$  and scenario  $\omega \in \Omega$ .

$$surplus_{\omega,t}^b = battery_{\omega,t}^{dc} - battery_{\omega,t}^c \quad \forall \omega \in \Omega, t \in T \quad (14)$$

The constraints (15) and (16) ensure the smoothing of the purchased energy and thus the avoidance of peaks. The parameter  $\Psi$  determines the maximum deviation of the purchased quantity from the previous hour. If this parameter tends towards infinity, no smoothing takes place; if it is zero, the same number of kWh must be purchased in every hour of a scenario.

$$energy_{\omega,t}^p \leq energy_{\omega,t-1}^p * (1 + \Psi) \quad \forall \omega \in \Omega, t \in [2:24] \quad (15)$$

$$energy_{\omega,t}^p \geq energy_{\omega,t-1}^p * (1 - \Psi) \quad \forall \omega \in \Omega, t \in [2:24] \quad (16)$$

As no further contribution to supply peaks is to be made, (17) defines the hours at which energy may be sold into the grid. The time span was limited to the demand peaks determined in section 4.3.

$$energy_{\omega,t}^s = 0 \quad \forall \omega \in \Omega, t \in [1,2,3,4,5,9,10,11,12,13,14,15,16,22,23,24] \quad (17)$$

All of the following restrictions deal with the management of the batteries.

The first general condition (18) is that batteries cannot contain more kWh than their maximum capacity at any time.

$$SOC_{\omega,t} \leq num^B * max^{Charge} \quad \forall \omega \in \Omega, t \in T \quad (18)$$

The second general condition (19) is that the SOC at the beginning of an hour is equal to the SOC at the beginning of the previous hour, minus the battery surplus during the previous hour. This applies to all hours except the first of the day.

$$SOC_{\omega,t} = SOC_{\omega,t-1} - surplus_{\omega,t-1}^b \quad \forall \omega \in \Omega, t \in [2:24] \quad (19)$$

For the first hour of the day, it is specified in (20) and (21) that it corresponds to the SOC at the end of the previous day. This is optimised across all scenarios  $\omega \in \Omega$ , thus limiting the planning to periods of one day into the future.

$$SOC_{\omega,t=1} = SOC_{eod} \quad \forall \omega \in \Omega \quad (20)$$

$$SOC_{eod} = SOC_{\omega,t=24} - surplus_{\omega,t=24}^b \quad \forall \omega \in \Omega \quad (21)$$

The last two constraints (22) and (23) allow the definition of safety capacities. These are determined by the parameter  $\Theta$ . If, for example,  $\Theta=0.1$  is applied, the battery is only discharged to the extent that at least 10% of the daily energy production remains in the battery at any time in each scenario, or 10% of the daily energy production of the storage capacity remains unused at any time in each scenario. This safety stock was introduced as the planning is done one day in advance on the basis of forecasts and therefore the probability is high that more energy has to be consumed or released than planned.

$$SOC_{\omega,t} \geq \Theta * \sum_{t \in T} prod_{\omega,t} \quad \forall \omega \in \Omega, t \in T \quad (22)$$

$$SOC_{\omega,t} \leq num^B * max^{Charge} - \Theta * \sum_{t \in T} prod_{\omega,t} \quad \forall \omega \in \Omega, t \in T \quad (23)$$

## 5 Results

In order to answer the research questions posed in chapter 3, several sensitivity analyses were carried out to determine the influence of demand smoothing, security

capacities, and selling prices. In order to be able to put the results of these analyses into relation, the daily costs (DC) and the peak to average ratio (PAR, Appendix A.) as used by Shewale et al (2020, p. 15) is used as a benchmark. To calculate this benchmark a house without any energy generation or storage is considered. Resulting in a benchmark DC of 6.31€ and PAR of 1.44.

Since the number of solar panels and batteries per house is optimized, but the number of wind turbines is independent of the number of houses, the costs were calculated for a different number of houses, while the number of wind turbines is fixed at a maximum of one. This approach makes the results easily scalable. Fig. 5 shows the results of this comparison. It can be seen that the costs drop sharply from 3 houses, then start to rise again and converge to the starting level. This is explained by the construction of a wind turbine starting from 3 houses. Above 7 houses, the influence of the comparatively stable production of the wind turbine is no longer great enough, which is why the amount of energy that must be purchased increases steadily from a number of more than 7 houses (App. C Fig. 12). Therefore, the ration of 7 houses per wind turbine is fixed in the further course.

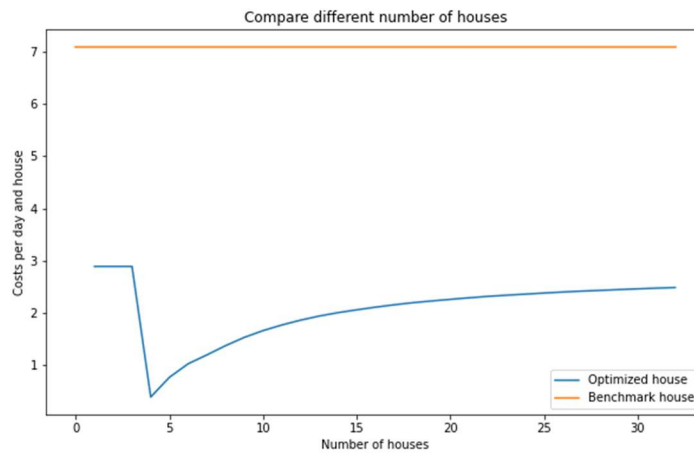


Figure 5 Number of houses

Next, the effects of limiting the change in purchased amount of kWh between successive hours is examined. As described in chapter 4,  $\Psi$  stands for the factor of the maximum possible change. The sensitivity analysis showed that the costs increase sharply from a value of  $\Psi = 2$ , but remain below the benchmark costs, even for  $\Psi = 0$  (Fig. 6). However, Fig 7 shows that the PAR decreases even further at lower values. Moreover, since the PAR at  $\Psi = 2$  is significantly higher than the benchmark, this is not a good solution, since peaks are not reduced but increased.  $\Psi = 0.1$  is a promising



candidate, as after this point PAR is nearly unchanged and with a value of 0.27 is significant below the benchmark PAR of 1.44.

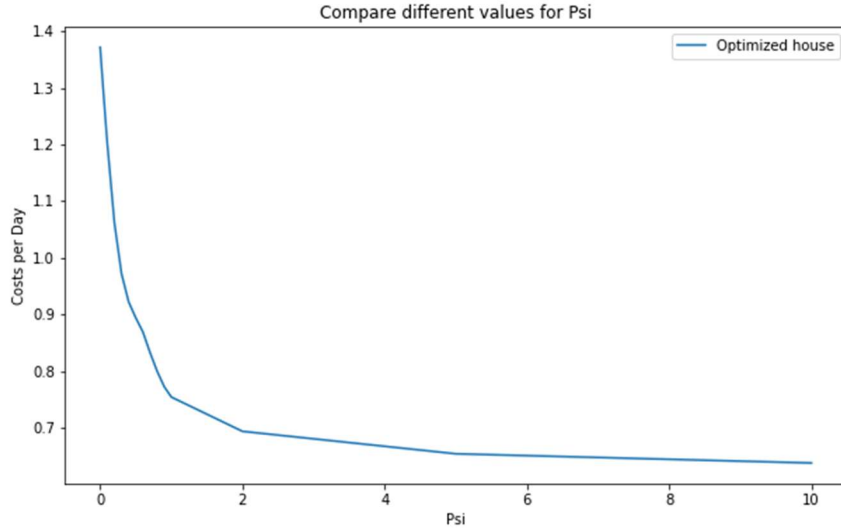


Figure 7 Costs of different psi

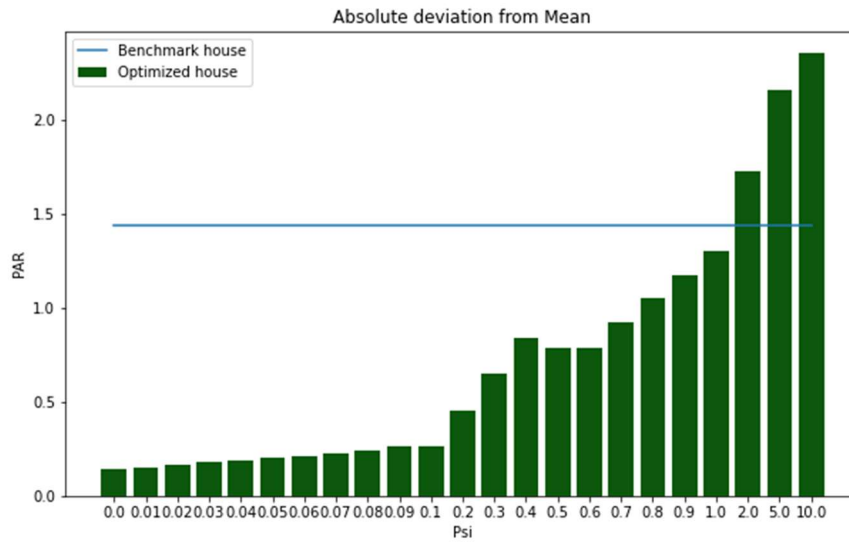


Figure 6 PAR of different psi

Lastly, the impact of a change in security capacity is considered. Since Li et al. (2016, pp. 6–7) showed that 24 hours in advance a fairly accurate prediction of energy production by solar plants can be achieved with less than 5% mae, this value serves as a reference. Fig 11 (App. C). Shown, that the cost for different values of  $\Theta$  increase linear. In order to maintain a certain degree of certainty, the final results are calculated with  $\Theta=0.1$ (two times the production forecast mae). Finally Fig. 8 shows the energy purchased per house in the benchmark and optimized case. It is clear to see that peaks are efficiently shaved. The final hybrid system is shown in Fig 13 (App. C).

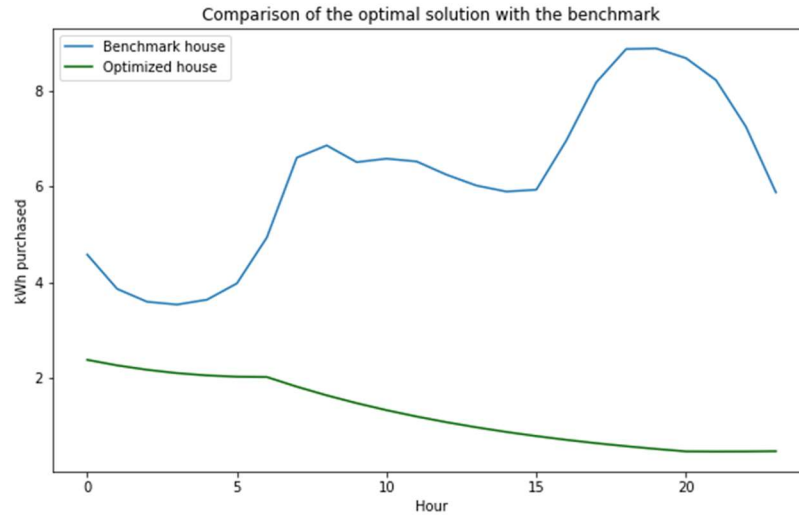


Figure 8 Optimization results

## 6 Discussion and Conclusion

The presented results are, after all, only valid to a certain extent. On the one hand, forecasts for production and demand are used, which creates a certain degree of uncertainty and can lead to deviations from the optimal solution in reality. However, this uncertainty should be absorbed as good as possible by the safety capacities of the batteries. It should also be noted that the power losses of solar panels and batteries are not directly considered in the model. To compensate for this, a lower performance level overall years is used, as well as relatively short amortisation periods well below the respective product guarantees. Another limitation is that although the setup can be scaled, the owners of the houses are not allowed to change the hybrid energy system architecture. This would require regulations and might not be possible in all countries. The major disadvantage of the presented method is that it leads to a significant reduction in costs compared to the benchmark, but at the same time yields significantly lower profits than an unregulated use of renewable energies. This is mainly due to the high number of batteries required, as well as the chosen restriction that energy can only be sold during certain hours, which severely limits the number of solar panels. However, since the intention of the work was to show that it is possible to shave peaks and be economic efficient, the research question posed is confirmed, as DC and PAR are significantly reduced.

In future work, the mathematical optimisation model could be supplemented by a simulation that tests the set-up in detail. In this way, individual decisions, such as the safety capacity, could be refined and the overall setup validated.

## A. Appendix

Hourly energy purchase smoothing ( $\Psi$ ) = Maximum permitted percentual change in purchase quantity compared to the previous hour.

E.g.  $\Psi = 0.1$  When energy purchase during hour  $t$  is 10 kWh, then energy purchase during  $t+1$  must be between 9 kWh and 11 kWh.

$$PAR = \frac{\text{Max Demand}}{\text{Average Demand}}$$

## B. Appendix

For solar panels, wind turbines and batteries, price research was carried out to identify characteristics of products in the higher value segment.

### Solar Panels

A maximum production of 0.4 kWh was assumed for the solar panels. In combination with an efficiency of 90%, this results in a maximum production of 0.36 kWh per solar panel. The costs are 400€ plus an installation and maintaining surcharge of 20%, leading to total cost of 480 €/panel. The amortization period is 10 years long. Taking into account the size of the panels and the average roof area, a limit of 30 panels per roof was set.

### Wind Turbines

A comparatively small wind turbine was used, which delivers a maximum of 12 kWh. Again an efficiency of 75% was chosen, leading to a maximum production of 9 kWh. The costs for turbine are 60.000 € plus a 20% installation and maintaining surcharge, leading to total costs of 72.000€. The amortization period is 10 years long.

### Batteries

A maximum storage capacity of 2.4 kWh was specified for the batteries. The batteries cost 600€, plus a 20% surcharge for installation and maintenance, resulting in a total cost of 720€. A limit of 6 batteries per household was determined as it is the maximum number for a lot of products. The amortization period is 5 years long.

## C. Appendix

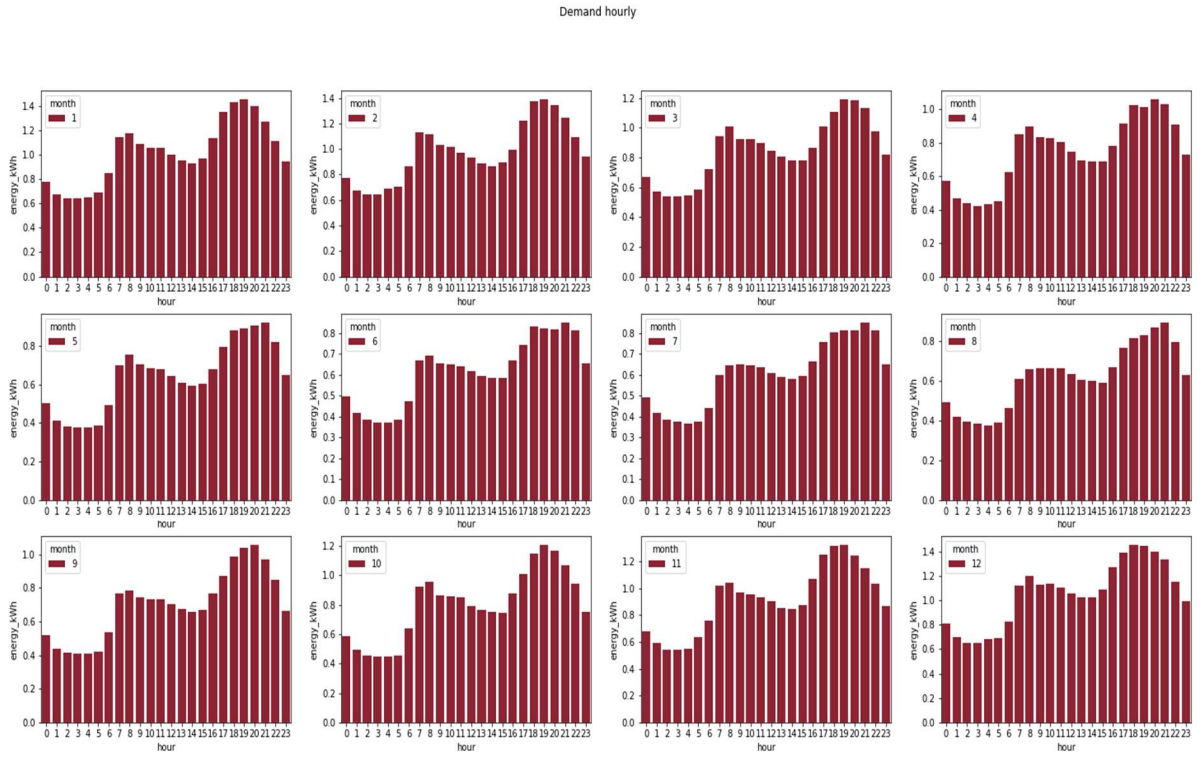


Figure 10 Average daily demand pattern

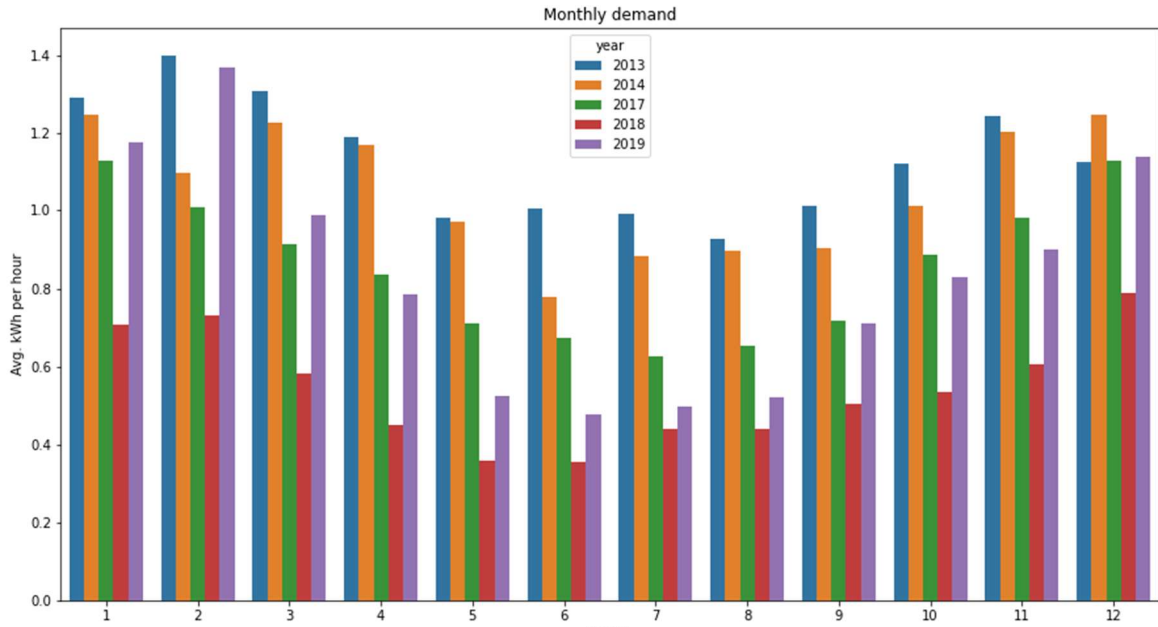


Figure 9 Average monthly demand pattern

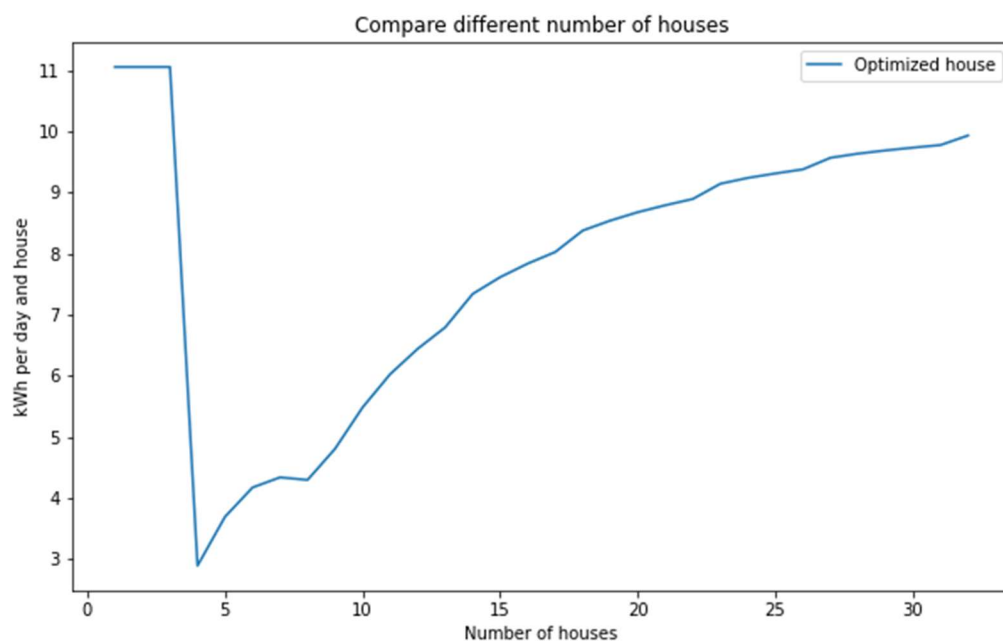


Figure 12 Demand for different numbers of houses

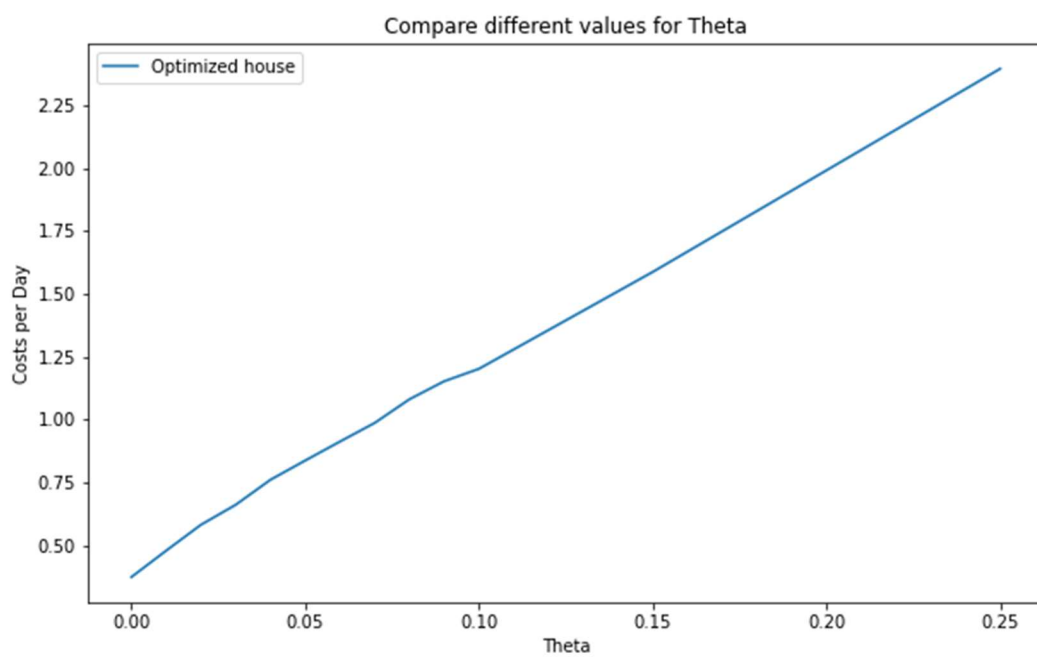


Figure 11 Costs for different Theta

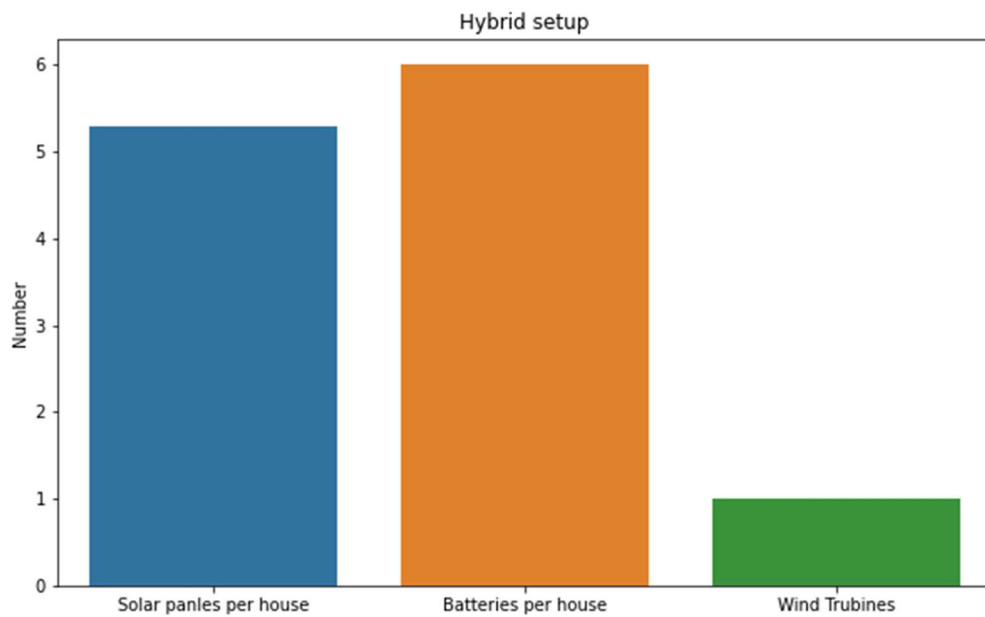


Figure 13 Hybrid energy setup

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Fabian Rehn

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Köln, den 14. March 2021

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