Active Distribution Networks

Roles and Challenges

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Abstract

Electricity demand is growing constantly. Due to rising climate awareness, the existing electricity production is being replaced with renewable energy sources (RES). Other energy transition-related changes, such as electric vehicles and electrification of heating also contribute to wider utilization of renewable energy sources, mainly due to rising electricity demand.

Unfortunately, due to the physical limitations of RES, no inertia is added to the electrical system with their implementation – inertia is lost with growing RES utilization. To cover the lost stability, flexibility adding technologies and solutions are needed. While there is a wide variety of flexibility-adding technologies, there are numerous technical limitations in the current electrical system, that are slowing down these implementations.

Our current electricity grids are built for a system where electricity can be thought of as a current flowing one-directionally from centralized power plants to the consumers via transmission lines and distribution networks. These are called passive distribution networks. While these networks have worked well until the current energy transition, they are not suitable to efficiently support, for example, the implementation of decentralized small-scale renewable energy production. Therefore, the alternative active distribution network (ADN) is presented and researched in this project.

The project presents some aspects of the energy transition and explores the potential for added flexibility of ADNs. Additionally, data analysis is conducted to support the findings. Optimization models are used to dive deeper into the potential benefits of ADNs in the author locations of Austria and the Czech Republic. The point of view on all of the above described topics for these two countries is included throughout the paper.

The applied models show that implementing and deploying ADNs is not only beneficial regarding the carbon goals, but also offers a feasible solution on the macro-level. The influences on the micro-level, especially within individual generation units, may however vary drastically depending on ambient conditions, such as current market dynamics and regulatory decision making. Furthermore it is determined and validated that the realistic degrees of freedom – rDoF – (the idea of which is introduced in the last chapter of the paper) within the system do play a crucial role in flexibility deployment on a national level.

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1 INTRODUCTION

Today's world does simply not run without electricity, and global consumption is growing constantly in every consumer type category. [1] The globally rising climatic awareness has motivated the EU to aim for carbon neutrality by 2050. This has introduced trends and challenges, one of them being the rapid decarbonization of energy production by implementing more renewable energy sources. [2] Unfortunately, these weather-dependent technologies are more unpredictable and less controllable than combustion-based technologies. [3] On top of these factors, the current power grid is burdened with a growing number of specific high-performance consumer units, such as electric vehicles (EVs).

Amongst many others, these three factors are fueling the structural change of the energy system known as energy transition, challenging current electrical systems and their features and capabilities. [4] However, the slow adaptation of the system changes is already causing widespread instability in the electricity grid: on 8 January 2021 at 14:05 CET the synchronous area of Continental Europe was split into two due to outages of several transmission network elements and components within a very short period. [5]

Our current electricity grids are built for a system where electricity flows can be idealized and thought of as one-directional streams from centralized power plants to the consumers through transmission lines and finally distribution networks. [6] These current, passive distribution networks (PDN), are neither to meet the needs and requirements of the energy transition, nor serve as a basis for implementing other decentralization technologies and solutions. Therefore, wide implementation of more fitting alternatives such as active distribution networks (ADN) is needed. [7,8]

The transition from PDN to ADN is well-founded in solving the energy transition-related challenges. The transition also brings whole new possibilities. These possibilities might include interlinking large-scale ADN, whereby serious monetary capital investments and strenuous physical system upgrades can be avoided or delayed even on the transmission grid level. [7,9] However, these projects face a diverse collection of challenges, ranging from economic, political, bureaucratic, and technical (to several deeper social) intricacies, which should be also studied. [10]

2 Objectives and Approach

The main goal of this paper is to research switching from PDN to ADN as a partial solution to the challenges caused by the current change in the electricity systems. First, some of the mentioned changes and challenges are examined, after which the theoretical difference between PDNs and ADNs are presented with some real-life implementation examples around the world. After that, the potential country-specific challenges related to ADN-implementations are researched in the author countries of the Czech Republic and Austria. The paper aims to reach its goal by answering the following hypotheses:

> **Hypothesis 1:**
> The current passive distribution network systems are not capable to serve as an implementational basis for the energy transition-related challenges.
>
> **Hypothesis 2:**
> Active distribution networks are partial solutions to the energy transition-related challenges in the electrical system.
>
> **Hypothesis 3:**
> Active distribution systems hold great potential (both monetary and emission goal related) in the Czech Republic and Austria.

The ongoing energy transition is causing multiple new challenges to the electricity system. It can be assumed, that a system based on the technology and understandings of a past era has trouble answering these kinds of challenges. This can be implemented/thought of as the base idea for the first hypothesis, which challenges the current and widely used energy distribution system. The second hypothesis targets the alternative solution for the problem introduced in the first hypothesis. Finally, the third hypothesis targets testing the findings of the first two hypotheses in a more precise and case-related environment.

Answers to these hypotheses are searched for by analysis of field data, which allows for conclusions on the identification of the hypotheses. For this purpose, up-to-date data and literature are used to arrive at useful and quantified statements, accrediting or rejecting the hypotheses. While most of the research is conducted as literature research, an additional optimization model is conducted to support the seek for an answer to the third hypothesis. The specific intricacies/implementational challenges for the two host countries are analyzed throughout the whole paper for each hypotesis.

3 PROBLEM ELABORATION AND QUANTIFICATION

This chapter describes and presents the quantifications of 3 different distribution network system related aspects that play huge roles in the energy transition. These are renewable energy sources (RES), electric vehicles (EV), and electrification of heating. Conclusions from their tendencies are drawn with a more precise descriptions of the situation in the two case study nations. After that, the chapter continues introduces the concept of flexibility in the energy system, as flexibility plays a key role in solving problems related to the energy transition, including the ones related to these 3 aspects.

3.1 Renewable Energy Sources (RES)

Many countries, especially in Europe, have provided subsidies and programs to support RES and especially PV installations, usually in form of investments, feed-in tariffs (TIF), or virtual net metering. [11] This has supported a rise in installations practically everywhere, especially within the consumer base due to the potentials of reducing personal/per-household electricity costs (running costs) and partial energy self-sufficiency. This, amongst many other reasons, has caused the investment costs of solar panels to drop to one-third between 2008 and 2018, feeding back into the installation amounts. [12] This tendency is also observable in the case of Austria and the Czech Republic. Their cumulative PV installations by MW are presented in Figure 1.

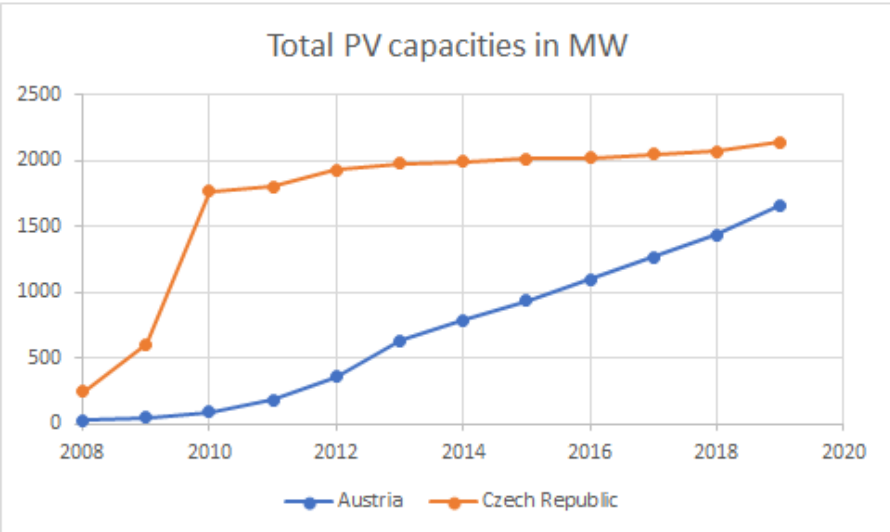

Figure 1: Cumulative PV installations in MW between 2008 and 2019. **[13-15]**

From Figure 1 it can be seen that CZ had an extremely sharp PV-installation boom in 2009 and 2010, which died out relatively quickly. This is due to their FIT program, which promised overcalculated subsidies. [16] Since then, multiple retrospective actions, taxes, and subsidy cuts have been launched to get the national-level expenses of the FIT system under control. Therefore, no new PV systems were installed since 2013, and investors are left feeling cheated and untrusting regarding future RES subsidy programs. [16,17] In 2018, PV covered only 28,2% out of RES production and about 4% of gross energy production, while costing the country (CZ) 66,8% or 1,15 trillion € of their RES subsidies. [16,18,19] RES subsidy and production distributions of CZ can be seen in Figure 2 below.

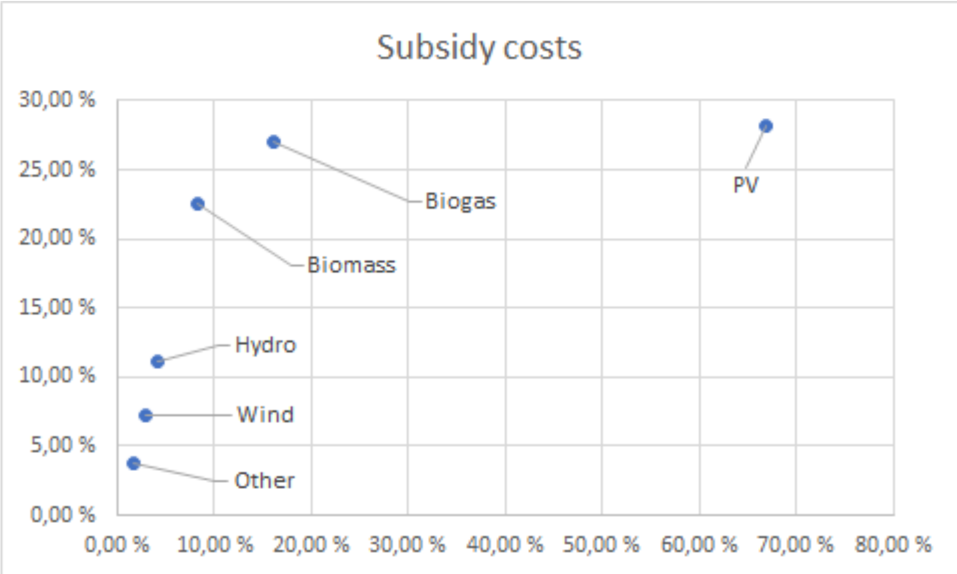

Figure 2: Subsidy and production distributions in CZ, 2018. [19]

The rapid and wide integration of decentralized RES in the distribution system causes great challenges, the most prominent being the intermittent peaks in a generation. [20] This unpredictable production behavior must be accounted for, as it results in harsher frequency and voltage fluctuations than before as well as a burden regarding the gross energy system. The underlying challenge is that the peaks in demand and supply do not overlap, so costly interim energy storage, consumption solution, or both are needed. [21] Adding greater electricity storage capacities to the already existing private PV systems is seen as one of the most potential options. Unfortunately, the battery system prices have not plummeted as harshly as PV unit prices, so they are not yet implemented as widely. [22] Altered and optimized demand-side response (DSR), or actual high-capacity energy storages can be seen as the most prominent large-scale alternative solutions.

Unlike the Czech Republic, Austria had a lot more restrained approach to support schemes. For example, they are still using the same Green Energy Act of 2012 which by amendments has caused a more controlled growth in PV installations. [17,23] Austria has also launched a program to reach 1 million rooftop solar panel installations by 2030 this year, so this steady growth in PV capacity can be predicted to continue. [24] When it comes to energy production in general, AT is doing better than CZ due to about 82% of its energy production being sourced from RES. In fact, AT aims to reach 100% RES energy production by 2030, as well as complete climate neutrality by 2040. [25]

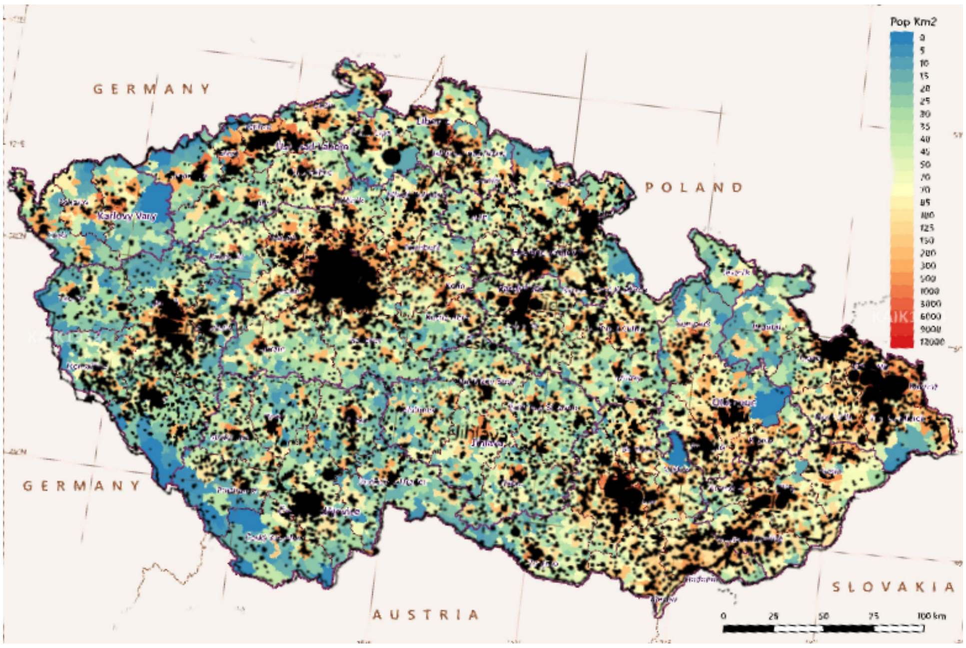

Figure 3: PV installation and population density in CZ, 2018. [23, 25]

Supporting the installation of new PV and other RES capacity does not only help to decarbonize the gross energy production, but allows consumers to lower their electricity bills and raise their independence over energy. These actions also help decentralize electricity production closer to consumption, as seen in Figure 3 above, where black dots represent PV installations, covering all Czech Republic's population hotspots. It also allows consumers who provide electricity to the grid, so-called prosumers, to upgrade from passive to active members of the distribution grid. Unfortunately, wider prosumer activity is currently restricted by the distribution system's physical and structural limitations. [26]

The widespread growth of weather-dependent and sometimes private-owned RES can be concluded to cause various challenges to the current electricity system. The biggest limitations for this growth can be found in the traditional control and distribution infrastructures, which are not able to support this kind of change on large scales due to physical and systemic restrictions. However, the needed upgrades in the distribution network could allow DSR to react more flexibly to the uneven electricity production and give the new prosumers a greater role for example in balancing production and consumption.

3.2 Electric Vehicles (EVs)

Electric Vehicles have been introduced to the consumer market for a couple of decades, gaining increasing attention. To support EVs forming a strong pillar in the electrification of the transport sector and the overall net-zero emission goal of Paris and other agreements by 2050, diverse subsidization schemes have been created. [27,28] The International Energy Agency (IEA) concludes that new electric car registrations still increased in major markets despite the economic effects of the current COVID pandemic. [29] Consumer spending increased as is deducible from Figure 4.

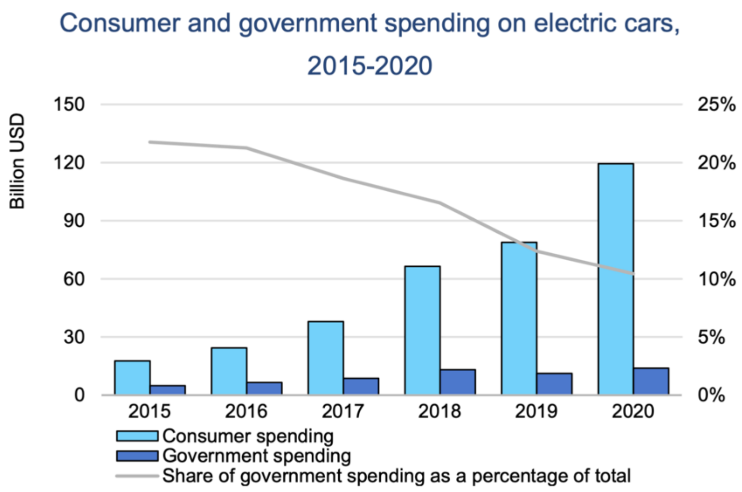

Figure 4: Consumer and government spending on EV over years (left axis nominal values, right axis percentages of government pending concerning total spending).

The influence of EVs on energy system operation can easily have detrimental effects on the energy system logistics when considering demand beak behavior and network stability. [20] Among residential consumer appliances, EVs of all types are considered to hold the highest average consumption performances (of roughly 27kW) with an average high-power capacity of roughly 15kW. These characteristics result in serious peaking effects. [30] Since each EV can be seen as an additional consuming unit released into the market, the continuous and increasing introduction of EVs increases net demand in the peak demand periods.

To quantify the impact of EVs on the energy system, the electricity demand concerning EV charging is analyzed. For this purpose, historic data from IAE is compiled and the predictions of IAE regarding two different scenarios are compared. The Stated Policy Scenario (STEPS) is mainly based on already existing and announced policies. The Sustainable Development Scenario (SDS) however is based on actually reaching the goals of the agreements. Left and right side of Figure 5 show the annual electricity demand of all EV types in the EU and global markets, respectively.

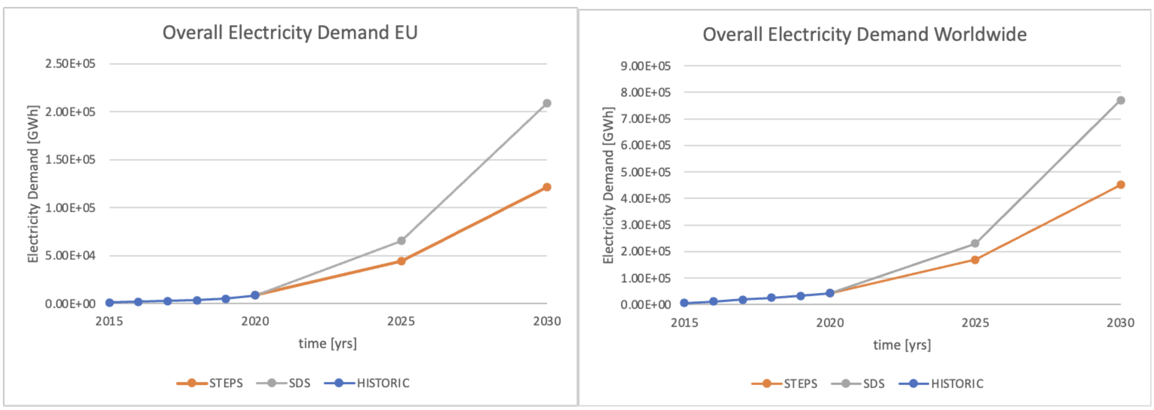

Figure 5: Left side: Electricity demand of all EV types within the EU over years (incl SDS and STEPS predictions). Right side: worldwide electricity demand of EVs.

According to Figure 5, it is visible that electricity demand in both EU and global markets is going to further rise due to the introduction of EVs, requiring significant additional generation. Due to the peak hour charging behavior of, over 50% of this additional generation would be utilized less than 5% of all time. [27] This utilization rate would be even lower if it were covered with RES, due to its unpredictable nature.

3.3 Electrification of Heating

The heating sector is getting increasingly united with the electricity sector every year. [31] This can be explained by a clear trend in the electrification of indoor heating, especially on the household market. This is due to an increasing amount of air heat pump (**AHP**) investments and installations. [32] An AHP can help cut the runtime of the main heating system, saving fuel and fuel costs. AHPs also give the tenants easy access to the cooling side of indoor temperature control, making them increase in popularity amongst house and apartment owners, and thus adding to the increase in electricity consumption and demand within buildings. [31]

In Figure 6 below, graphs for yearly AHP sales and total installations can be seen for both Austria and Czech Republic. In both countries, the yearly AHP sales and therefore installations follow increasing trends. Between 2009 and 2018, Austria and the Czech Republic have had a yearly increase of about 10k and 15k installations, and the total installations had grown by 90k and 133k units, respectively.

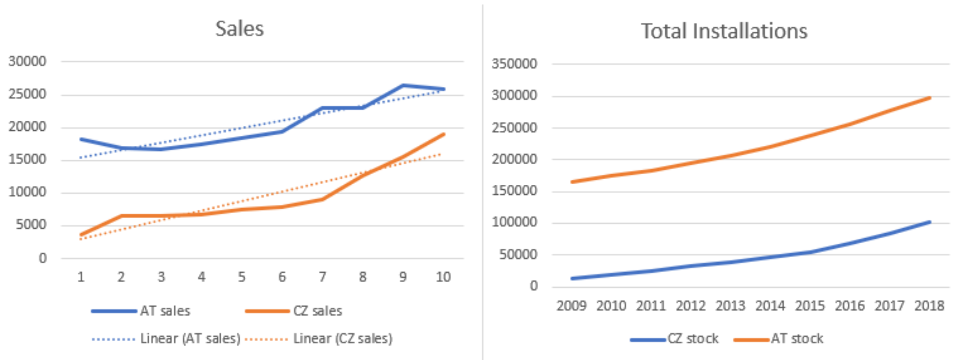

Figure 6: Yearly AHP sales [left] and total installations [right] in AT and CZ. [33]

In addition to the versatile, easy-to-install, and inexpensive AHPs, there are many electric options for the main heating systems on the market, such as air-water heat pumps, electric boilers, and geothermal solutions. These solutions are gaining increasing amounts of attention, especially in sparsely populated areas, due to their environmental and economic benefits. [33] Therefore, an increase in electricity consumption due to the electrification of heating could be predicted within the upcoming years. To reach the European climate goals, it can be assumed that this increase is covered by RES.

4 PROPOSED SOLUTION: ACTIVE DISTRIBUTION NETWORKS

The energy system features listed in the earlier chapter – as well as many other energy transition-related changes, hold diverse challenges. For example, electricity systems hold a built-in feature against changes in electrical current, called electrical system inertia. [34] This characteristic is based on the inertia in heavy power plant turbines, large rotating generators, and huge industrial motors, which tend to continue rotating even after their energy source is cut. [35] Unfortunately, RES technologies do not contribute to the electrical system inertia due to nonexistent or light-weighted turbines and generators, especially when they are decentralized. [20,36] In classical electricity systems, inertia provides some well-needed stability in the constant balancing of production and consumption of electricity. [34,36] To cover this major challenge, alternative stabilizing solutions are needed.

Electrical system stability can be reached and supported with different kinds of electrical system flexibility. [36] This electrical system feature can be partially used to cover missing system inertia, and in this study, it is seen as a partial solution to all major energy transition-related problems, trends, and challenges stated in the earlier chapter. According to the Office of Gas and Electricity Markets UK, flexibility can be defined as *"modifying generation and/or consumption patterns in reaction to an external signal (such as a change in price) to provide a service within the energy system*". [37] This umbrella term covers many actions, technologies, and schemes, all aiding to balance the peaks of production and consumption in the electricity system. [38]

Technologies that add flexibility can be categorized based on the electricity system sector they are found in. [39] These categories are listed in Table 1 with some examples. As it can be seen from Table 1, some technologies can be seen to be part of multiple categories, either by default or by different methods of use and exploitation. for example, EVs can be seen as demand-side management tools if they are charged at the moments when there is excess production, and as sector coupling tools by turning electricity into the transportation of goods and people. [40]

Table 1: Types of flexibility with examples.

Generation:	distributed generation, on-off generation
Demand-side management:	smart appliances, EVs
Sector coupling:	heating, hydrogen, EVs
Transmission:	inter-areal coupling, international trade
Distribution:	ES technologies, bidirectional wiring
Storage:	Small scale batteries, pumped hydro stations

Deployment of flexibility enables more efficient and feasible economic and environmental usage of resources also in systems with regular inertia. It also enables the utilization of any energy technology, with fewer limitations and curtailments. [38] Because focusing on one type of flexibility is rarely feasible, multiple types are needed simultaneously. Additionally, many flexible solutions carry diverse additional benefits. For example, distributed generation, smart appliances, EVs, and ES technologies carry the potential to transform passive consumers into active prosumers, who may provide both energy and flexibility services to the system on both local and national levels. [41]

Current distribution networks are typically passive (PDN), meaning that there is no electricity generation linked to them. Electricity is delivered to the distribution networks from one or multiple transmission networks and distributed to consumers. [10] While this base model of distribution network systems has been sufficient until now, it is challenged by the current energy transition-related technologies, trends, and challenges. [9]

An alternative to the traditional PDNs is an active distribution network (ADN). While the distinction between ADN and smart grids is not consistent between papers and publications, the simplest definition for an ADN is that it holds at least some electricity production within itself. [42] The biggest benefits of ADNs are that they support further integration of so-called distribution generation, create a strong base for smart grid implementations, and create a whole new scale of possibilities for adding flexibility into the electrical system. On the other hand, ADNs also demand these technologies, solutions, and features to work properly. [42,43]

5 MODEL

To quantify the effects of the adaption of the current grids (by integration of any sort of ADN), several possible scenarios are modeled by a solving unit commitment problem of the supply side (energy generation) on the national level using linear optimization. The same scenarios are used for Austria as well as for the Czech Republic to enable useful comparisons and conclusions regarding the differences in the two regions. Hence it is crucial to stress that the models are (as soon to be shown by the governing limitations) generalized to a degree that allows expansion and adaptation to both regions and a timely and efficient implementation. This includes different aggregation steps leading to loss of information regarding microeconomics: many crucial economical micro-processes (for example influence of arbitration of capital investment/ accounting depreciation) and technological limitations (bus and transformer capacities or ramping limitations) are disregarded and traded off. However, the generalization is kept to a level that should still allow insight into the governing macro-dynamics of the energy market.

The conclusions drawn from these models should therefore be seen as a general motivation to developing ADNs and should motivate further research on this topic. The conclusions should in no way be seen as accurate predictions of different factors (costs for example) of possible future outcomes. The models only allow as accurate predictions as inhibited by their limitations (which will be discussed shortly). Overall, three different scenarios are modeled for the two regions for a 2020 timeframe resulting in six different configurations. A second optional timeframe for 2030 (with the same static model parameters – generation assumptions) can be implemented by adjusting model parameters and applying and implementing a model accounting for the increase in demand.

Timeframes:

Timeframe 1: Current state – Base model

Timeframe 2 (optional): State of systems in 2030 considering the national emission roadmaps and energy incentives (zero-emission for generation in AT).

Scenarios per model:

Scenario 1: Business as usual System (BAU) consideration without ADN Flexibility

Scenario 2: System with flexibility on Macro level (centralized ADN integration – Austria does already include instances such as ES (hydrodynamical))

Scenario 3: System with flexibility on Micro-level (decentralized energy system, decentralized ADN integration – peak shaving capability, etc.)

Table 2 gives an idea of the scopes of each model by stating the key considerations and main features. The modeling is conducted on an hourly basis over a timespan of representative three months for each configuration as limited by model complexity. The modeled timespan spans from 08.30.2018 to 11.30.2018 (due to national load data availability). Based on the obtained data predictions for yearly nominal figures can be made by multiplying accordingly.

Table 2: Scopes and key considerations considered for the three scenarios.

Scenario 1	- No additional considerations (simple unit commitment for current load matching with full generation consideration).
Scenario 2	- Integration of EV (V2G) storage capability on national level as an addition to existing ES (hydro pumped). Set at 8% of overall EV battery capacity. - Limited decentralized peak shaving capability, according to EV charging and other residential and industrial load management (motivated by the consideration of the capabilities of bigger regional communities). Set at 6%
Scenario 3	- Integration of EV storage as an addition to existing ES, set at 57% - Limited decentralized peak shaving capability set at 15% - Centralized peak shaving capability (motivated by the consideration of grid-to-instance communication and support – limited by regulation) governed by the model. Energy loads other than the baseload are assumed to be transposable to a level dictated by the transposing factor, set at 10%

For the mathematical model description please see the annex. The unit commitment problem is solved as follows: both the cost and the emission dependency of the supply/generation side are linearly modeled, where a minimum in costs is set as the objective. This mainly results from the fact that arriving at a non-linear analytical model with the complexity of the two underlying countries is neither feasible nor abetted by the available resources.

The availability of data puts the following general constraints on the model. All data is obtained mainly from databases of national organizations and NGOs (such as IEA, Entso-e, etc.), for further detail please see the references. The Levelized costs of energy – LCOE – (operational costs) of each supplier is approximated with the following considerations: (i) a full depreciation of all fossil-based plants is assumed (accounting depreciation of the overnight capital costs, fix O&M costs, and any other capital investment linked cost factors are not regarded) and (ii) the remaining useful lifetime of the plants is not considered. The variable costs (marginal costs) are therefore assumed to be dependent on the discounted capital costs, O&M costs, fuel prices, and the carbon price as per the following equation. Index i denotes the energy type.

$$LCOE_i = C_{cap,i} + C_{O\&M,i} + C_{fuel,i} + C_{CO_2,i} \tag{1}$$

The data for LCOE calculation is obtained from **[29,44]** using a uniform interest rate of 4% (for discounting), a standard carbon price of 26.31 EUR/MWh and a USD/EUR Exchange rate of 0.877 (2020 average) from **[45]**. The merit order of the supply is thereby affected/influenced by the discounted capital costs, O&M costs, fuel prices, the fuel types, overall plant capacities, and CO_2 emission factors.

The national generation capacities are obtained from **[46]** for the year 2019 and in the case of Austria validated via **[47]**. Generation capacity is aggregated for easier handling purposes and partly due to data availability into the categories listed in the results. Since the LCOE is calculated for current values (2020) and the generation capacity data is only lagging one year (2019), the modeling is conducted for 2020 with the load data of 2018.

The national overall demand data (main input) is obtained from **[48]** with an hourly resolution (15min resolution available). The amount of hourly transposable load is calculated with the following formula, which in reverse yields the base load for assumed residual flexibility, where l_h is the hourly actual load, $l_{b,h}$ the hourly baseload, $l_{tEV,h}$ the hourly transposable load linked to EVs and $l_{tr,h}$ the hourly residual transposable load (index h denotes respective hours). This allows for flexibility quantification of load behavior in scenarios 2 and 3.

$$l_h = l_{b,h} + l_{tr,h} + l_{tEV,h} \quad (2)$$

Data on EV consumption is derived from **[49]**, data on national overall nominal EV amounts from **[50,51]** and average storage capacities from **[30,52]**. This allows for the quantification of additional storage capacities in scenarios 2 and 3. The input of the priority fed renewables wind and solar energy are obtained from **[53]** with an hourly resolution. For the mathematical quantification of the peak shaving and peak increasing (for the 2030 timeframe) please see the annex. In addition to the limitations imposed by data availability, further considerations must be made regarding the main constraints:

- No power line capacity constraints are regarded.
- No transferring and transformation capacities and losses are regarded.
- No transferring and transformation costs are regarded.
- Only overall and aggregated energy balance is considered, detailed information is therefore lost. A disaggregation allows for conclusions to be drawn on plant level.
- No other environmental costs and constraints are considered (other particle emissions, water pollution, etc.).
- All models are based on the current environment state (meaning current demand market etc.) and therefore give insights into possible adaptation scenarios for the current market.

6 RESULTS

The following chapters briefly lay out the results for the two countries going into detail only where significant observations can be made. The results are discussed for both countries separately. The Energy Category "other renewables" includes energy generation from waste plants and landfill gas.

6.1 CZECH REPUBLIC

6.1.1 Costs & Emissions

The left side of Figure 7 shows the overall costs, the right side the overall emissions for the different ADN implementation scenarios (denoted by S1 through S3 for the rest of the paper). Both figures include nominal numbers (on the left respective axis) and the values in percentages normed to the BAU scenario (on the right respective axis). Regarding the costs, the partial implementation of S2 of the ADN only leads to relatively small cost savings as opposed to the more progressed scenario S3. A cost-saving of 650Mio. EUR is predicted (the accuracy of this data is questionable), which imposes a mere 92% of the original costs. To fully understand the context and the magnitude of these numbers, plant utilization will have to be taken into account. A more realistic cost saving of appr. 50 000 EUR is observable in S2.

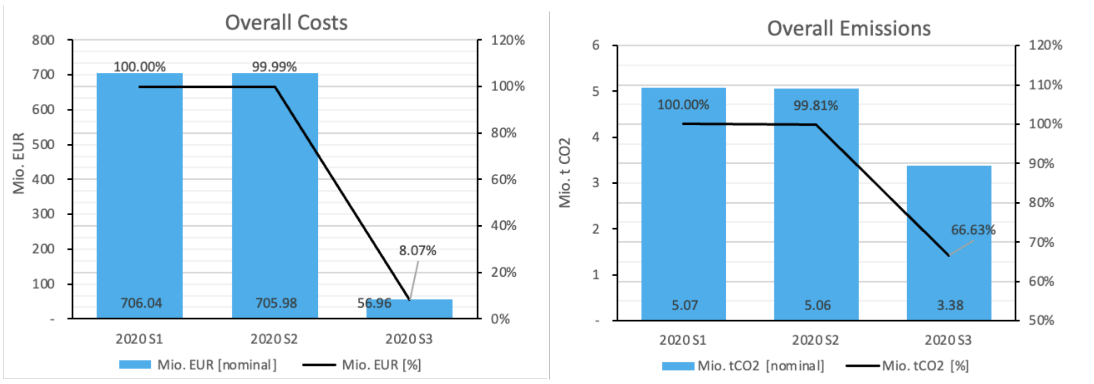

Figure 7: Left side: overall costs per scenario (with additional percentage axis on the right side, normed to S1) 2020 Czech Republic; right side: overall emissions per scenario (with additional percentage axis on the right side, normed to S1) 2020 Czech Republic.

The S3 Scenario does lead to a reduction of appr. 2.31 Mio t of Carbon Dioxide, a significant amount considering current regulative guidelines and goals. A comparison with Austria follows.

6.1.2 Energy Mix

The analysis of the overall energy mix allows for further and deeper elaboration on the data presented on costs and emissions. Figure 8 shows on the left side the overall national Energy mix for scenario S1 and on the right side the overall national Energy mix for scenario S3. Since the data for scenario M2 is only insignificantly different from that of S1, it is only included in the annex. Due to relatively wide flexibility deployment on the network side (flexibility increase due to ES increase) substantially, the altered energy mix is obtained for S3.

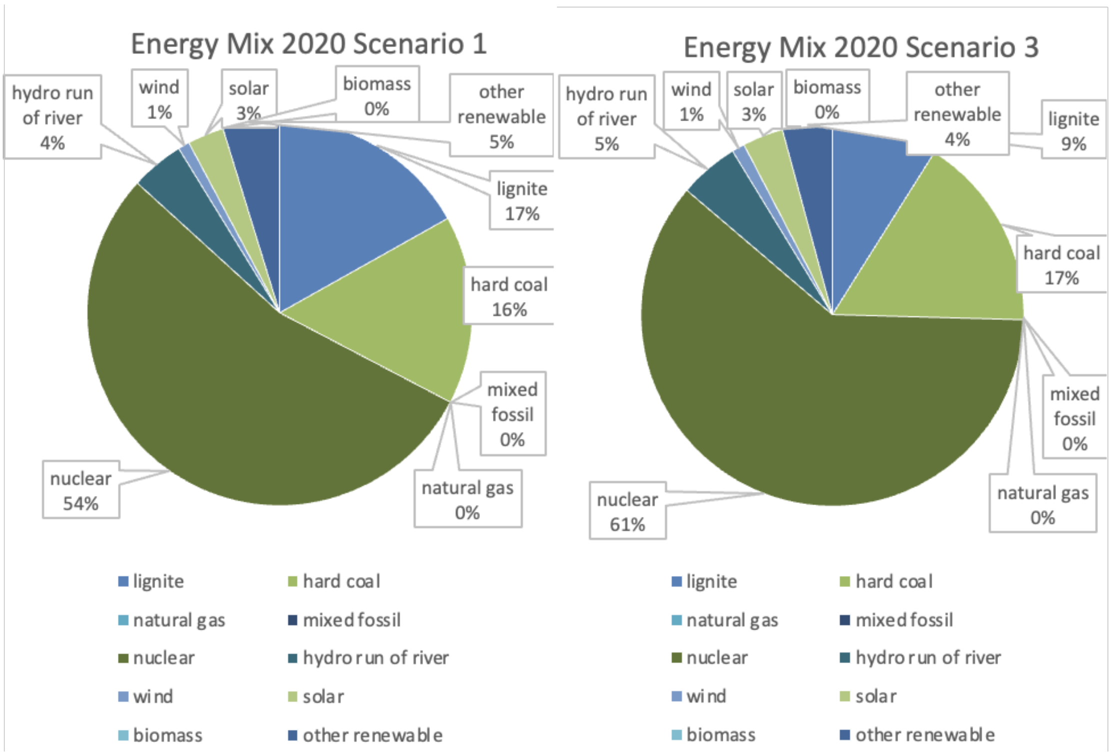

Figure 8: Left side: Energy mix for scenario S1 2020 Czech Republic (percentages shown for orientation); right side: Energy mix prediction for scenario S3 2020 Czech Republic.

A significant increase in the nuclear energy category, along with an increase in the run of river and hard coal-related generation and curtailment of mainly lignite-related generation (as well as waste and landfill gas related generation) is observable for Scenario 3 in comparison to S1. The baseload is hence covered with more environmentally friendly generation amounting to the drop in emissions as the influence of carbon costs plays a significant role in the merit order. Nuclear-related generation increases from appr. 54% to 61%, lignite-related generation drops 8 points from the original 17% of Scenario 1.

6.1.3 Plant utilization

The plant utilization u_i (index i denotes the plant type/Energy type, index h the respective hour/timestep) is calculated by the following formula, where the actual energy output of the plant accumulated over the entire modeling timespan is divided by the maximum possible nominal energy output of the given plant over the modeling timespan T – a utilization factor of 100% means that the plant was running 100% of the time.

$$u_i = \frac{\sum_{h=1}^{T} P_{actual,h,i}}{\sum_{h=1}^{T} P_{nominal\ capacity,i}} \tag{3}$$

Figure 9 shows the plant utilization by energy category for Scenarios S1 through S2. As per equation 3, solar and wind utilization figures are only a fraction of the overall possible generating capacity due to environmental insecurity and fluctuation. The priority feed-in constraint accounts for the constant of these categories through the three scenarios.

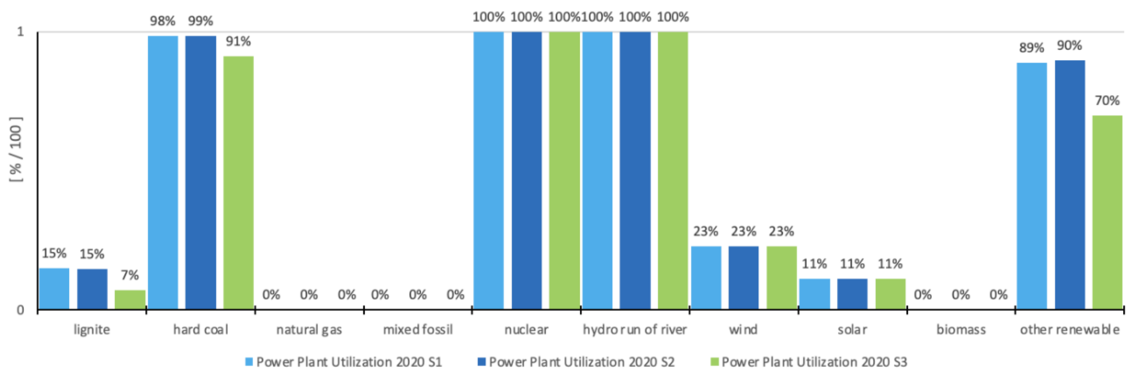

Figure 9: Power plant utilization for scenarios S1 through S3 (predictions) for the Czech Republic, 2020.

As deducible from Figure 9, the nuclear and run of river-related generation is fully exhausted. Similar observations can be made for hard coal and other renewable-related generation, which in S3 all dropped in comparison to S1. The biggest relative drop is observable in a lignite-related generation an over 50% drop (from 15% to 7%).

In order to obtain a more coherent conclusion, the Idea of "realistic degrees of freedom" (rDoF) is introduced (which is applicable in parallel to the simple degrees of freedom DoF):

> The rDoF is meant to take into account any factor that eliminates specific degrees of freedom, which are considered degree of freedom only formally. Therefore, these degrees of freedom do not truly contribute to the DoF of the underlying system and are therefore referred to as "fake DoF": The rDoF is governed by the priority feed-in constraint as well as the fact that the lowest instances and highest instances in the merit order are either base-load-satisfier (running all the time either way) or can be disregarded due to full curtailment and are therefore not really in the competing dynamic domain and are considered "knocked out".

The normal DoF regarding energy categories of the Czech Republic is in the case of this model equal to ten, as all energy types can theoretically be utilized to an arbitrary degree. The rDoF on the other hand is the normal DoF minus the "fake DoF". The rDoF in this case is therefore governed by lignite, hard coal and landfill and waste related generation (as the only actively competing players through all scenarios) and is therefore 4. The plant utilization further has a great impact on overall system costs.

6.2 AUSTRIA

6.2.1 Costs & Emissions

The left side of Figure 10 shows the overall costs, the right side the overall emissions for the different ADN implementation scenarios. Again, both figures include nominal numbers (on the left respective axis) and the values in percentages normed to the BAU scenario (on the right respective axis). The overall system costs of appr. 809 Mio Eur are reduced to a mere appr 56 Mio EUR for S3, a more realistic cost reduction can however be observed for scenario 2 with a reduction of almost 5 Mio Eur. This would account for a yearly saving of appr. 20 Mio. EUR.

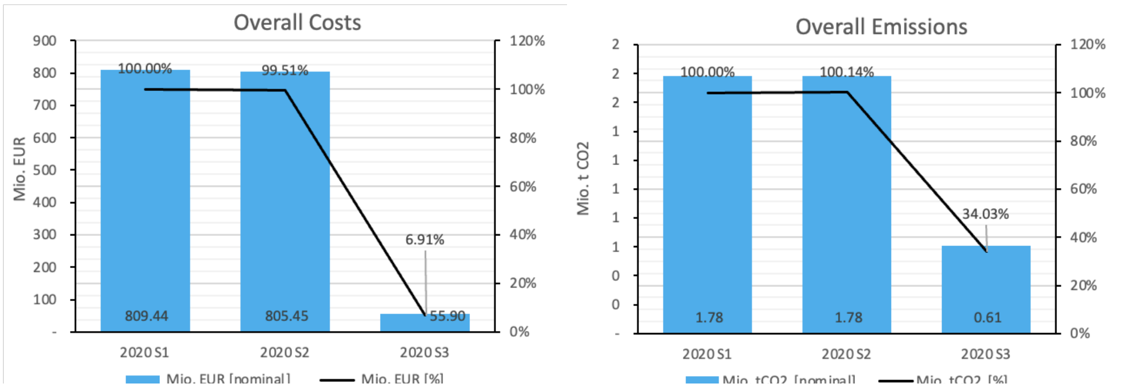

Figure 10: Left side: overall costs per scenario (with additional percentage axis on the right side, normed to S1) 2020 Austria; right side: overall emissions per scenario (with additional percentage axis on the right side, normed to S1) 2020 Austria.

A reduction in emissions to 34% of the BAU scenario can be reached in the S3 scenario – a much greater reduction compared to the Czech Republic (66.3%) mainly due to higher flexibility already embedded in the system: more renewable capacity (namely run of river hydro generation) but also greater storage capacities. Hence, the rDoF (as shortly derived for Austria) plays an additional crucial role in national flexibility deployment ability and capability. This allows for the emissions to be reduced to a level of about 2.4 Mio t nationally over one year, which in comparison to the Czech Republic is significantly lower.

6.2.2 Energy Mix

The left side of Figure 11 the overall national Energy mix for scenario S1, the right side the overall national Energy mix for scenario S3. A Reduction in natural gas (by 12 points) and hard coal (2 points) related generation is observable. This is complemented mainly by a 12-point increase (to 80%) of the run of river renewable generation.

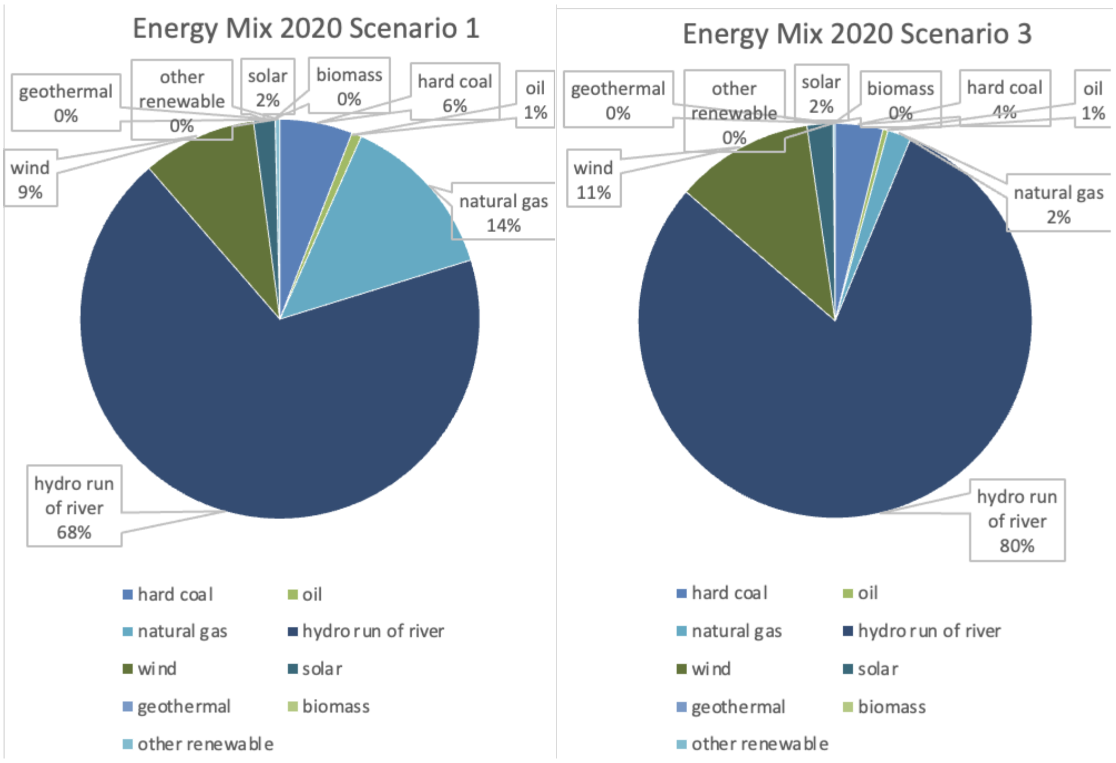

Figure 11: Left side: Energy mix for scenario S1 2020 Austria (percentages shown for orientation); right side: Energy mix prediction for scenario S3 2020 Austria.

It is crucial to mention that due to the higher number of rDoF in comparison to the Czech Republic, the Energy mix is altered by greater extents. The main load covering is accounted for by the renewable run of river generation. In the BAU scenario, fossil generation makes out only appr. 21%, which is further reduced appr. 7% in Scenario 3.

6.2.3 Plant utilization

Figure 12 shows the plant utilization by energy category for Scenarios S1 through S2. In the case of Austria, none of the plants are utilized 100% in any scenario. Main drops in utilization are observable in the fossil categories oil, hard coal, and natural gas. The relative drop in the run of river-related generation (a drop of appr 5%) is much lower than the relative drops in fossil generation (appr. 54% on average over the three categories). This hints that the integration of additional renewable technologies (such as run of river plants) linked with higher relative capital costs is only curtailed by fossil generation to a finite extent. This increases relative zero-emission flexibility.

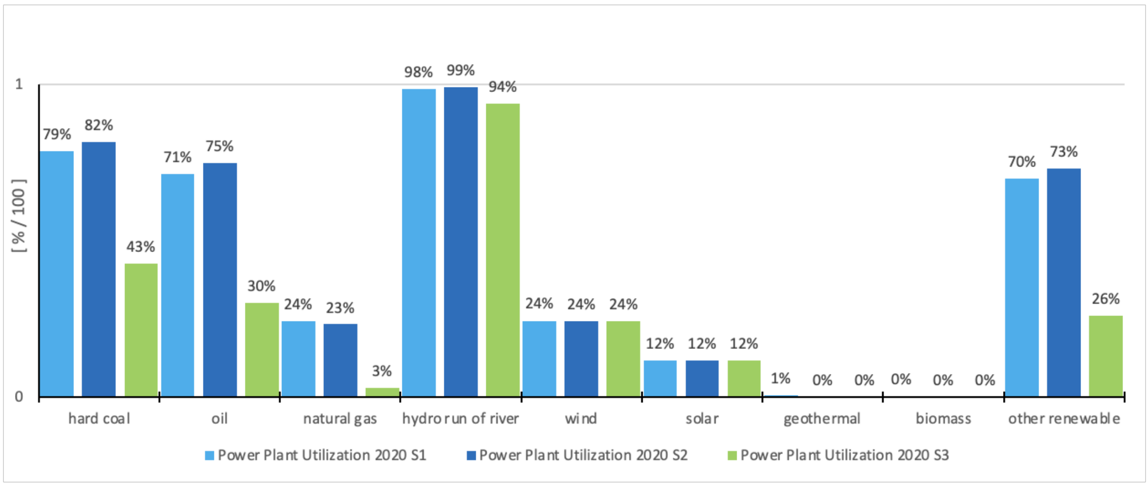

Figure 12: Power plant utilization for the scenarios S1 through S3 (predictions) for Austria, 2020.

Additionally, the window of competition is therefore increased in comparison to the Czech Republic: the rDoF for Austria is equal to 6, which is 50% more than in the case of the Czech Republic (only two out of the eight categories are "knocked out"). This is results in a much greater system side ability of flexibility deployment.

Concludingly the importance of installed renewables in short-term flexibility deployment (with no/little network side reaction time) can be stressed, as higher overall capacities allow a higher rDoF. Higher installed renewable technologies that have the potential of full utilization further aid flexibility deployment.

7 CONCLUSIONS

When it comes to the ongoing energy transition, different electrical system-related challenges arise. One of the biggest chalange is the electrical system instability caused by the wider implementation of renewable energy sources, mostly due to their lack of inertia. On top of replacing existing parts of the current energy production to RES, the trends of wider usage of EVs and electrical heating systems are capable to cause an even stronger need for deployment of flexibility. While there are many ways to add flexibility to the energy system, the current passive distribution network systems do not offer enough implementational access points for solutions to these energy transition-related challenges.

Active distribution networks offer a strong framework for flexibility adding technologies, holding great and effective potential in both author countries of Austria and the Czech Republic. The applied models show that implementing and deploying flexibility thorugh ADNs is not only beneficial regarding the carbon goals, but also offers a feasible solution on the macro-level. The influences on the micro-level and especially within individual generation units may vary drastically depending on ambient conditions, such as current market dynamics and regulatory decision making. Furthermore, and probably most importantly, it is determined and validated that the realistic degrees of freedom within the system do play a crucial role in flexibility deployment on a national level.

The merit order is externally influenced by carbon costs as the main instrument. However, the arsenal could and should be extended on a regulatory level, by introducing the idea of interdicting and prohibiting the application of accounting depreciation in the generation sector. Even though this proposed instrument is not regarded in the models, it could increase the relative feasibility of newly installed renewable generation compared to old power plants (therefore leading to a modified, more modern and suitable merit order). This possibility should be regarded, assessed, and analyzed with care. The utilization of many fossil fuels and therefore carbon-related categories and individual plants would be governed by more natural market dynamics, in combination with the aid of regulatory carbon price adjustment. This could result in a significantly more environmentally friendly and technologically up-to-date generation, both in the short and long run.

Not discussed, yet interesting for further research is the topic of to which specific extent ADN and similar peak-shaving technologies can aid the overall goals on regional or micro-levels. Topics that arise for further research from this paper are the practical integration of ADNs and the regulatory and legal aspects of integration – especially after the introduction of new energy community legal structures by the European Union. The effects of such regulatory interventions need to be assessed carefully to enable predictions, and actively aid and consult on the sociological and economical aspects of related decision making.

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9 ANNEX

9.1 Additional Data

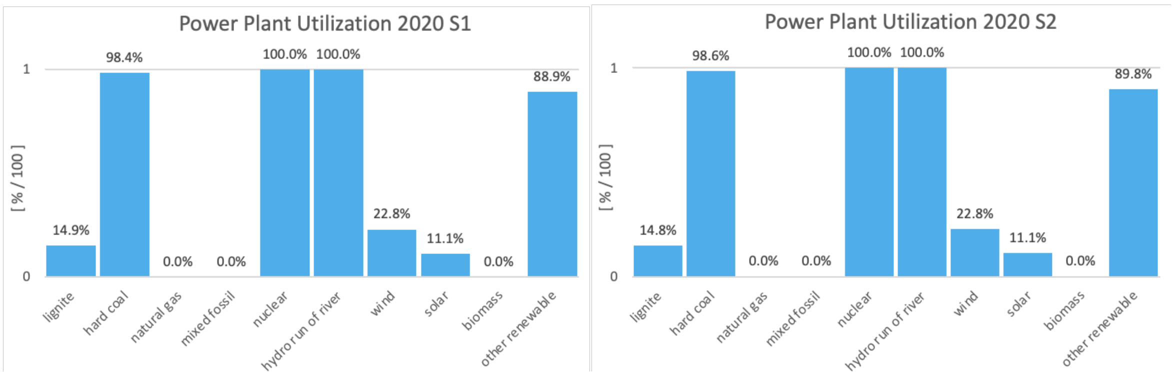

Figure 13: Left: detailed power plant utilization of the Czech Republic for Scenario 1; right: detailed power plant utilization of the Czech Republic for Scenario 2.

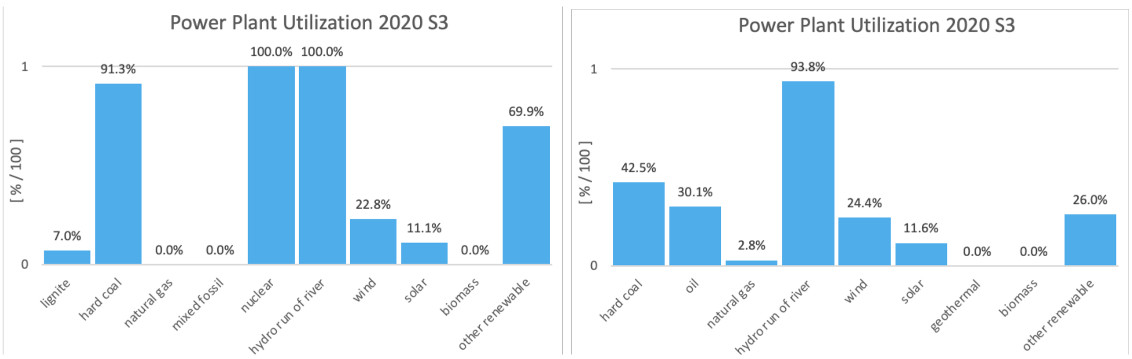

Figure 14: Left: detailed power plant utilization of the Czech Republic for Scenario 3; right: Left: detailed power plant utilization of Austria for Scenario 3.

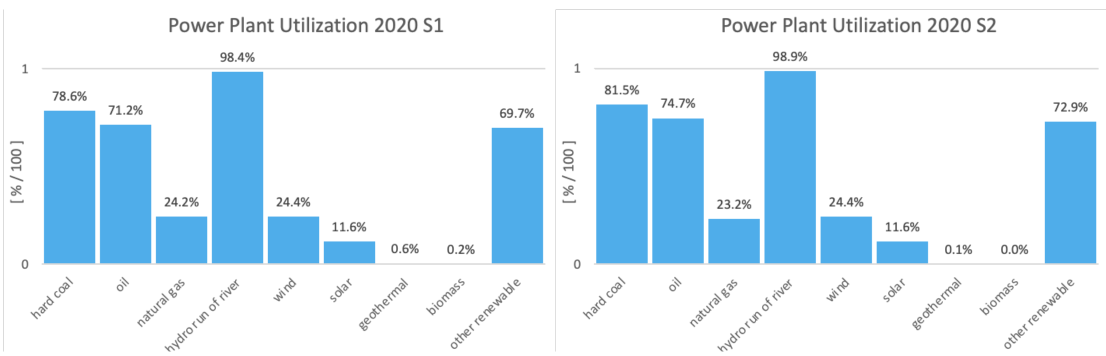

Figure 15: Left: detailed power plant utilization of Austria for Scenario 1; right: detailed power plant utilization of Austria for Scenario 2.

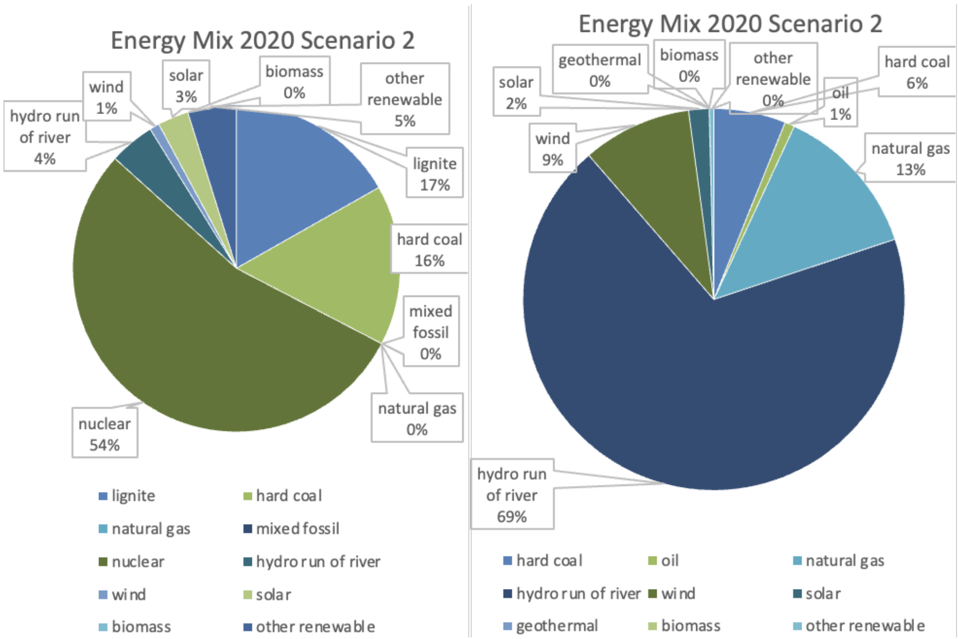

Figure 16: Left: Energy mix for scenario S2 2020 Czech Republic; right: Energy mix for scenario S2 2020 Austria.

9.2 Mathematical model description

The mathematical description/logics of the respective scenarios are defined as follows. The modeling is conducted via Python using Pyomo in combination with the Gurobi™ Optimizer as the solver. The denotation of the respective hour/timestep happens with the index t in the context of the optimization model description and with index h in the context of data manipulation to avoid misleading (considering index t standing for the transposable fraction in latter context).

Here, $P_{j,t}$ represent the optimal commitment of energy category j in hour t, $LCOE_j$ the LCOE of the respective energy category. The optimal hourly commitments are limited by the max installed plant capacity $P_{j,max,t}$ (as input Parameters), the hourly commitments of the renewables hydro $P_{PV,t}$ and wind $P_{W,t}$ are priority fed into the model as input parameters. The hourly load l_t is fed as an input Parameter and must match the generation of the system. The addition of Energy storage yields the hourly SOC (State of Charge) term, where SOC_t is limited by the national reservoir incl. pumped storage capacity SOC_{max} (as an input parameter). The net hourly turbinating and pumping performances $P_{turb,t}$ and $P_{pump,t}$ are limited by the ramping limits $P_{turb,max,t}$ and $P_{pump,max,t}$ and are accounted for in the load matching condition ($P_{turp,t}$ acts as generation hence are positive,

$P_{pump,t}$ as additional load hence negative) by considering the respective (turbinating and pumping) efficiencies η_{pump} and η_{turb} (all as input Parameters). Further the starting SOC SOC_{start} must match the terminal SOC SOC_{end}.

Scenario 1:

Objective function: (4)

$$\min_{P_j} C_{total} = \sum_{t=1}^{T} \sum_{j} \left(P_{j,t} LCOE_j\right)$$

Constraints: (5)

$$l_t = \sum_j P_{j,t} + P_{turp,t} - P_{pump,t}$$
$$0 \le P_{turb,t} \le P_{turb,max,t}$$
$$0 \le P_{pump,t} \le P_{pump,max,t}$$
$$0 \le P_{j,t} \le P_{j,max}$$
$$P_{PV,t} = P_{PV,priority,t}$$
$$P_{W,t} = P_{W,priority,t}$$
$$SOC_t = SOC_{t-1} + P_{pump,t}\eta_{pump} - \frac{P_{turp,t}}{\eta_{turb}}$$
$$SOC_t \le SOC_{max}$$
$$SOC_{start} = SOC_{end}$$

Scenario 2:

Additionally, to Scenario 1, the SOC limitation is extended by the SOC of feasibly attached EV to the grid with V2G capability, hence SOC_{max} is the sum of the original national reservoir incl. pumped storage capacity SOC_{hydro} and the net capacity of accessible EV battery storage SOC_{EV} (as input parameters).
Additionally, Scenario 2 includes an external DSR that is modifying the hourly load input independently as described in "data manipulation mathematical description"

Objective function: (6)

$$\min_{P_j} C_{total} = \sum_{t=1}^{T} \sum_{j} \left(P_{j,t} LCOE_j\right)$$

Constraints: (7)

$$l_t = \sum_j P_{j,t} + P_{turp,t} - P_{pump,t}$$

$$0 \leq P_{turb,t} \leq P_{turb,max,t}$$
$$0 \leq P_{pump,t} \leq P_{pump,max,t}$$
$$0 \leq P_{j,t} \leq P_{j,max}$$
$$P_{PV,t} = P_{PV,priority,t}$$
$$P_{W,t} = P_{W,priority,t}$$
$$SOC_t = SOC_{t-1} + P_{pump,t}\eta_{pump} - \frac{P_{turp,t}}{\eta_{turb}}$$
$$SOC_t \leq SOC_{max} = SOC_{hydro} + SOC_{EV}$$
$$SOC_{start} = SOC_{end}$$

Scenario 3:

Scenario 3 includes the possibility of including load shifting in the optimization (internal DSR). Here γ_C and γ_{DC} represent the percentages of the net hourly load that are considered as transposable on the macro-level (perfect macro-micro communication is assumed for optimal DSR) for shifting off and on loads on the demand side respectively. Affecting the total hourly SOC SOC_t, these transposed loads are considered by considering the respective battery charging and discharging efficiency η_{pump} (as an input parameter). γ_C and γ_{DC} are limited by the maximum respective transposing factors $\gamma_{C,max}$ and $\gamma_{DC,max}$ as input parameters. These values are governed by the findings resulting from eq. 2 and consider the baseload, the EV-related transposable load, and the residual transposable load.
The scenario includes the external DSR as an addition.

Objective function: (8)

$$\min_{P_j} C_{total} = \sum_{t=1}^{T} \sum_{j} \left(P_{j,t} LCOE_j\right)$$

Constraints: $l_t(1 - \gamma_C + \gamma_{DC}) = \sum_j P_{j,t} + P_{turp,t} - P_{pump,t}$ (9)

$$0 \leq P_{turb,t} \leq P_{turb,max,t}$$
$$0 \leq P_{pump,t} \leq P_{pump,max,t}$$
$$0 \leq P_{j,t} \leq P_{j,max}$$
$$P_{PV,t} = P_{PV,priority,t}$$
$$P_{W,t} = P_{W,priority,t}$$
$$SOC_t = SOC_{t-1} + P_{pump,t}\eta_{pump} - \frac{P_{turp,t}}{\eta_{turb}} +$$
$$\gamma_C l_t \eta_{battery} - \frac{\gamma_{DC} l_t}{\eta_{battery}}$$
$$SOC_t \leq SOC_{max} = SOC_{hydro} + SOC_{EV}$$

$$SOC_{start} = SOC_{end}$$
$$0 \leq \gamma_C \leq \gamma_{C,max}$$
$$0 \leq \gamma_{DC} \leq \gamma_{DC,max}$$

9.3 Data manipulation mathematical description

First, the external DSR used in Scenario 2 and 3 is discussed. The data modification takes the hourly load l_h as an input and creates the modified hourly load $l_{h,modified}$ for every timestep to be fed as input for the optimization. Here, K stands for the harmonizing timespan where the average load $l_{avg,K}$ is determined. For the sake of simplicity (and resources), the average load is assumed to be approximating the value the load would be statistically fluctuating around in the case of residential EV-linked peak shaving (peak shaving and valley filling).

$$l_{avg,K} = \frac{\sum_{h=1}^{K} l_h}{K} \tag{10}$$

The factor ε stands for the percentage of deviation of l_h from the harmonized average that can be "shaved".

$$l_{h,modified} = l_h + \left(l_h - l_{avg,K}\right)(1 - \varepsilon) \tag{10}$$

Fig XXX shows the output of the two data manipulation algorithms: the green dotted line represents the modified shaved (by peak shaving and valley filling) hourly load values over a sample of 48 hours, the blue dotted line the modified increased hourly load.

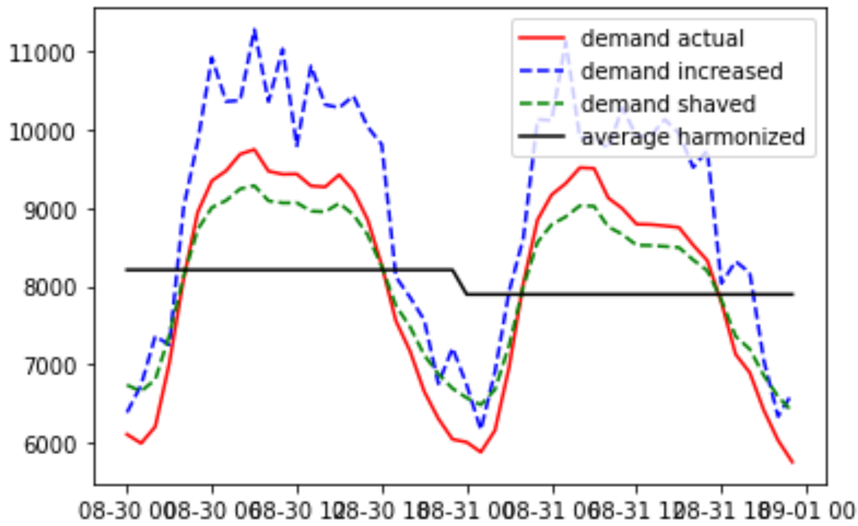

Figure 17: Demand shaving and increasing over 48 hours (harmonized average is the horizontal black line).

9.4 Directory of Figures

9.5 Directory of Tables

9.6 Code snippet

This part includes a sample code snippet for scenarios 1, 2 and 3. The snippets were taken along the process and are therefore not the final codes – they might include bugs and smaller inconsistencies. They are merely for the purpose of display the principle of implementation.

9.6.1 Scenario 1

```
# -*- coding: utf-8 -*-
"""
Created on Sun Jun 13 09:34:12 2021

@author: Bence F. Hegyi BSc

df ... data frame
dc ... data column [array]
"""

# -*- coding: utf-8 -*-
"""
Seminar Paper
Model AUSTRIA
Scenario 1-1
"""

from pyomo.environ import *

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import pyomo.environ as pyo


#----------------SETTING MAIN PARAMETERS---------------------------------------
T = 3*720                                  #one day = 24, one week = 168, one month =
720, one year = 8784
timesteps = np.arange(T)

c_CO2 = 26.31                           # EUR/tCO2
turb_efficiency = 0.9                   # efficiency of hydro turbines
# transp_fraction = 0.1                   # how much of the demand is flexible
battery_efficiency = 0.95               # efficiency of charging and discharging
batteries of EVs

EV_to_grid = 0                        # fraction of EV2gridcapacity to total
EVbankcapacity


modeled_country = 'AT'                  # country code: can be either AT or CZ


#----------------LOADING and defining POWERPLANT SPECS-------------------------
#loading and formatting powerpland specs
df_poweplants = pd.read_excel('Power_Plants_spec.xlsx')
df_storage_spec = pd.read_excel('Storage_spec.xlsx')

hydro_max = df_storage_spec['hydro '+modeled_country].values.tolist()
SOC_max_hydro = hydro_max[0]
EV_max = df_storage_spec['EV '+modeled_country].values.tolist()
SOC_max_EV = EV_max[0]

plant_name     = df_poweplants['name'].values.tolist()
plant_capacity = df_poweplants['Net capacity '+modeled_country].values.tolist()
capital_cost   = df_poweplants['Capital cost'].values.tolist()
O_M_cost       = df_poweplants['O&M'].values.tolist()
fuel_cost      = df_poweplants['Fuel (el)'].values.tolist()
```

```
carbon_factor  = df_poweplants['CO2 emission factor'].values.tolist()

power = {}
cap_cost = {}
O_M = {}
fuel_price = {}
c_factor = {}

for i in range(len(plant_name)):
    power[plant_name[i]] = plant_capacity[i]
    cap_cost[plant_name[i]] = capital_cost[i]
    O_M[plant_name[i]] = O_M_cost[i]
    fuel_price[plant_name[i]] = fuel_cost[i]
    c_factor[plant_name[i]] = carbon_factor[i]

# calculate marginal costs of energy supply units
MC = {}                     # marginal costs in EUR/MWh
LCOE = {}                   # LCOE in EUR/MWh
emissions = {}              # emissions in tCO2/MWh
for n in plant_name:
    MC[n] = fuel_price[n] + c_factor[n] * c_CO2
    LCOE[n] = cap_cost[n] + O_M[n] + fuel_price[n] + c_factor[n] * c_CO2
    emissions[n] = c_factor[n]



#----------------LOADING INPUT DATA for DEMAND, WIND and SOLAR-----------------
# load input data
df = pd.read_excel('Input.xlsx')
load = df['demand '+modeled_country+' actual [MW]']
PV = df['generation '+modeled_country+' solar [MW]']
Wind = df['generation '+modeled_country+' wind [MW]']

#modifying load data to shaved



#modifying load data to growing


#----------------CREATING PYOMO MODEL------------------------------------------
model = ConcreteModel()
model.J = range(T-1)
model.x = Var(plant_name, timesteps, within=NonNegativeReals)

model.P_pump = Var(timesteps, within=NonNegativeReals, bounds=(0,0.03*(SOC_max_hydro)
+ SOC_max_EV * EV_to_grid), initialize=0)
model.P_turb = Var(timesteps, within=NonNegativeReals, bounds=(0,0.03*(SOC_max_hydro)
+ SOC_max_EV * EV_to_grid), initialize=0)
# model.g_c = Var(timesteps, within=NonNegativeReals, bounds=(0,transp_fraction),
initialize=0)
# model.g_dc = Var(timesteps, within=NonNegativeReals, bounds=(0,transp_fraction),
initialize=0)
model.SOC = Var(timesteps, bounds=(0, SOC_max_hydro + SOC_max_EV * EV_to_grid),
initialize=0)


# defining objective function
obj_expr = sum(LCOE[n] * model.x[n, t] for n in plant_name for t in timesteps)
model.obj = Objective(expr=obj_expr,
                      sense=minimize)


# defining constraints
def SOC_power_constraint_rule(model, t):
    return model.SOC[t+1] == model.SOC[t]+model.P_pump[t]*turb_efficiency-
model.P_turb[t]/turb_efficiency#+model.g_c[t]*load.loc[t]*battery_efficiency-
model.g_dc[t]*load.loc[t]/battery_efficiency
model.SOC_con = Constraint(model.J,
                           rule=SOC_power_constraint_rule)


def SOC_end_constraint_rule(model,t):
    return model.SOC[T-1] == model.SOC[0]
model.SOCend_con = Constraint(timesteps,
                              rule = SOC_end_constraint_rule)


def power_constraint_rule(model, n, t):
```

```
    return model.x[n, t] <= power[n]

model.power_con = Constraint(plant_name,
                             timesteps,
                             rule=power_constraint_rule)


def load_constraint_rule(model, t):
    return sum(model.x[n, t] for n in plant_name) + model.P_turb[t] - model.P_pump[t]
== load.loc[t] #* (1-model.g_c[t]+model.g_dc[t])
model.load_con = Constraint(timesteps,
                            rule=load_constraint_rule)


def wind_power(model, t):
    return model.x['r_wind',t] == Wind.loc[t]
model.wind_con = Constraint(timesteps,
               rule = wind_power)


def pv_power(model, t):
    return model.x['r_solar',t] == PV.loc[t]
model.pv_con = Constraint(timesteps,
               rule = pv_power)

model.dual = pyo.Suffix(direction=pyo.Suffix.IMPORT)

opt = SolverFactory('gurobi', solver_io="python")
opt_success = opt.solve(model)



#----------------------------DATA EVALUATION-----------------------------------
# model.display()

# print("Duals")
# for c in model.component_objects(pyo.Constraint, active=True):
#     print("   Constraint", c)
#     for index in c:
#         print("      ", index, model.dual[c[index]])

# get values of optimization variables
PowerThermal = pd.DataFrame(index=timesteps, columns=plant_name)
for t in timesteps:
    for n in plant_name:
        PowerThermal.loc[t, n] = model.x[n, t].value


#calculate total emssions and total costs
total_emissions = 0
total_costs = 0

for t in timesteps:
    for n in plant_name:
        total_emissions += PowerThermal.loc[t,n]*emissions[n]
        total_costs += PowerThermal.loc[t,n]*LCOE[n]


#calculate aggregated commitment of each energy type and output to excel
committed = {}

for i in range(len(plant_name)):
    summ = 0
    for t in timesteps:
        summ += PowerThermal.loc[t,plant_name[i]]

    committed[plant_name[i]] = summ

df_output_committed = pd.DataFrame(data=committed, index=[0])
df_output_committed = (df_output_committed.T)

df_output_committed.to_excel('output_commitment.xlsx')


#get values for SOC for plotting
SOC_df = pd.DataFrame(index=timesteps, columns = ['SOC'])
for t in timesteps:
    SOC_df.loc[t] = model.SOC[t].value
# PowerThermal= pd.concat([PowerThermal, SOC_df], axis=1)
```

```
# plant_name.append('SOC')

print("Total emissions =", total_emissions)
print("Total costs =", total_costs)
```

9.6.2 Scenario 2

```
# -*- coding: utf-8 -*-
"""
Created on Sun Jun 13 09:34:12 2021

@author: Bence F. Hegyi BSc

df ... data frame
dc ... data column [array]
"""

# -*- coding: utf-8 -*-
"""
Seminar Paper
Model AUSTRIA
Scenario 1-1
"""

from pyomo.environ import *

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import pyomo.environ as pyo


#----------------SETTING MAIN PARAMETERS--------------------------------------
T = 3*720                                 #one day = 24, one week = 168, one month =
720, one year = 8784
timesteps = np.arange(T)

c_CO2 = 26.31                         # EUR/tCO2
turb_efficiency = 0.9                 # efficiency of hydro turbines
# transp_fraction = 0                 # how much of the demand is flexible
battery_efficiency = 0.95             # efficiency of charging and discharging
batteries of EVs

EV_to_grid = 0.08                     # fraction of EV2gridcapacity to total
EVbankcapacity
shaver = 0.06

modeled_country = 'AT'                # country code: can be either AT or CZ


#----------------LOADING and defining POWERPLANT SPECS-------------------------
#loading and formatting powerpland specs
df_poweplants = pd.read_excel('Power_Plants_spec.xlsx')
df_storage_spec = pd.read_excel('Storage_spec.xlsx')

hydro_max = df_storage_spec['hydro '+modeled_country].values.tolist()
SOC_max_hydro = hydro_max[0]
EV_max = df_storage_spec['EV '+modeled_country].values.tolist()
SOC_max_EV = EV_max[0]

plant_name     = df_poweplants['name'].values.tolist()
plant_capacity = df_poweplants['Net capacity '+modeled_country].values.tolist()
capital_cost   = df_poweplants['Capital cost'].values.tolist()
O_M_cost       = df_poweplants['O&M'].values.tolist()
fuel_cost      = df_poweplants['Fuel (el)'].values.tolist()
carbon_factor  = df_poweplants['CO2 emission factor'].values.tolist()

power = {}
cap_cost = {}
O_M = {}
fuel_price = {}
c_factor = {}
```

```
for i in range(len(plant_name)):
    power[plant_name[i]] = plant_capacity[i]
    cap_cost[plant_name[i]] = capital_cost[i]
    O_M[plant_name[i]] = O_M_cost[i]
    fuel_price[plant_name[i]] = fuel_cost[i]
    c_factor[plant_name[i]] = carbon_factor[i]

# calculate marginal costs of energy supply units
MC = {}                      # marginal costs in EUR/MWh
LCOE = {}                    # LCOE in EUR/MWh
emissions = {}               # emissions in tCO2/MWh
for n in plant_name:
    MC[n] = fuel_price[n] + c_factor[n] * c_CO2
    LCOE[n] = cap_cost[n] + O_M[n] + fuel_price[n] + c_factor[n] * c_CO2
    emissions[n] = c_factor[n]



#----------------LOADING INPUT DATA for DEMAND, WIND and SOLAR-----------------
# load input data
df = pd.read_excel('Input.xlsx')
load = df['demand '+modeled_country+' actual [MW]']
PV = df['generation '+modeled_country+' solar [MW]']
Wind = df['generation '+modeled_country+' wind [MW]']

#modifying load data to shaved
load_shaved = []
avg=[]
k=0
for n in range(int(len(load)/24)):
    summ=0
    for i in range(24):
        summ += load[k+i]
    avg.append(summ/24)
    k += 24

k=0
for n in range(len(avg)):
    for i in range(24):
        deviation = load[k+i] - avg[n]
        if load[k+i] < avg[n]:
            load_shaved.append(avg[n] + (1-shaver) * deviation)
        if load[k+i] > avg[n]:
            load_shaved.append(avg[n] + (1-shaver) * deviation)
    k+=24
load = load_shaved


#modifying load data to growing


#----------------CREATING PYOMO MODEL------------------------------------------
model = ConcreteModel()
model.J = range(T-1)
model.K = range(T)
model.x = Var(plant_name, timesteps, within=NonNegativeReals)

model.P_pump = Var(timesteps, within=NonNegativeReals, bounds=(0,0.03*(SOC_max_hydro)
+ SOC_max_EV * EV_to_grid), initialize=0)
model.P_turb = Var(timesteps, within=NonNegativeReals, bounds=(0,0.03*(SOC_max_hydro)
+ SOC_max_EV * EV_to_grid), initialize=0)
# model.g_c = Var(timesteps, within=NonNegativeReals, bounds=(0,transp_fraction),
initialize=0)
# model.g_dc = Var(timesteps, within=NonNegativeReals, bounds=(0,transp_fraction),
initialize=0)
model.SOC = Var(timesteps, bounds=(0, SOC_max_hydro + SOC_max_EV * EV_to_grid),
initialize=0)


# defining objective function
obj_expr = sum(LCOE[n] * model.x[n, t] for n in plant_name for t in timesteps)
model.obj = Objective(expr=obj_expr,
                      sense=minimize)


# defining constraints
def SOC_power_constraint_rule(model, t):
    return model.SOC[t+1] == model.SOC[t]+model.P_pump[t]*turb_efficiency-
model.P_turb[t]/turb_efficiency
```

```
model.SOC_con = Constraint(model.J,
                           rule=SOC_power_constraint_rule)


def SOC_end_constraint_rule(model,t):
    return model.SOC[T-1] == model.SOC[0]
model.SOCend_con = Constraint(timesteps,
                              rule = SOC_end_constraint_rule)


def power_constraint_rule(model, n, t):
    return model.x[n, t] <= power[n]

model.power_con = Constraint(plant_name,
                             timesteps,
                             rule=power_constraint_rule)


def load_constraint_rule(model, t):
    return sum(model.x[n, t] for n in plant_name) + model.P_turb[t] - model.P_pump[t]
== load[t]
model.load_con = Constraint(model.K,
                            rule=load_constraint_rule)


def wind_power(model, t):
    return model.x['r_wind',t] == Wind.loc[t]
model.wind_con = Constraint(timesteps,
               rule = wind_power)


def pv_power(model, t):
    return model.x['r_solar',t] == PV.loc[t]
model.pv_con = Constraint(timesteps,
               rule = pv_power)

model.dual = pyo.Suffix(direction=pyo.Suffix.IMPORT)

opt = SolverFactory('gurobi', solver_io="python")
opt_success = opt.solve(model)



#-----------------------------DATA EVALUATION-----------------------------------
# model.display()

# print("Duals")
# for c in model.component_objects(pyo.Constraint, active=True):
#     print("   Constraint", c)
#     for index in c:
#         print("      ", index, model.dual[c[index]])

# get values of optimization variables
PowerThermal = pd.DataFrame(index=timesteps, columns=plant_name)
for t in timesteps:
    for n in plant_name:
        PowerThermal.loc[t, n] = model.x[n, t].value


#calculate total emssions and total costs
total_emissions = 0
total_costs = 0

for t in timesteps:
    for n in plant_name:
        total_emissions += PowerThermal.loc[t,n]*emissions[n]
        total_costs += PowerThermal.loc[t,n]*LCOE[n]


#calculate aggregated commitment of each energy type and output to excel
committed = {}

for i in range(len(plant_name)):
    summ = 0
    for t in timesteps:
        summ += PowerThermal.loc[t,plant_name[i]]

    committed[plant_name[i]] = summ
```

```
df_output_committed = pd.DataFrame(data=committed, index=[0])
df_output_committed = (df_output_committed.T)

df_output_committed.to_excel('output_commitment.xlsx')


#get values for SOC for plotting
SOC_df = pd.DataFrame(index=timesteps, columns = ['SOC'])
for t in timesteps:
    SOC_df.loc[t] = model.SOC[t].value
# PowerThermal= pd.concat([PowerThermal, SOC_df], axis=1)
# plant_name.append('SOC')

print("Total emissions =", total_emissions)
print("Total costs =", total_costs)
```

9.6.3 Scenario 3

```
"""
Created on Sun Jun 13 09:34:12 2021

@author: Bence F. Hegyi BSc

df ... data frame
dc ... data column [array]
"""

# -*- coding: utf-8 -*-
"""
Seminar Paper
Model AUSTRIA
Scenario 1-1
"""

from pyomo.environ import *

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import pyomo.environ as pyo



#----------------SETTING MAIN PARAMETERS---------------------------------------
T = 3*720                                  #one day = 24, one week = 168, one month =
720, one year = 8784
timesteps = np.arange(T)

c_CO2 = 26.31                         # EUR/tCO2
turb_efficiency = 0.9                 # efficiency of hydro turbines
transp_fraction = 0.1                 # how much of the demand is flexible
battery_efficiency = 0.95             # efficiency of charging and discharging
batteries of EVs

EV_to_grid = 0.57                      # fraction of EV2gridcapacity to total
EVbankcapacity
shaver = 0.15

modeled_country = 'AT'                # country code: can be either AT or CZ



#----------------LOADING and defining POWERPLANT SPECS-------------------------
#loading and formatting powerpland specs
df_poweplants = pd.read_excel('Power_Plants_spec.xlsx')
df_storage_spec = pd.read_excel('Storage_spec.xlsx')

hydro_max = df_storage_spec['hydro '+modeled_country].values.tolist()
SOC_max_hydro = hydro_max[0]
EV_max = df_storage_spec['EV '+modeled_country].values.tolist()
SOC_max_EV = EV_max[0]

plant_name     = df_poweplants['name'].values.tolist()
plant_capacity = df_poweplants['Net capacity '+modeled_country].values.tolist()
capital_cost   = df_poweplants['Capital cost'].values.tolist()
O_M_cost       = df_poweplants['O&M'].values.tolist()
```

```
fuel_cost      = df_poweplants['Fuel (el)'].values.tolist()
carbon_factor  = df_poweplants['CO2 emission factor'].values.tolist()

power = {}
cap_cost = {}
O_M = {}
fuel_price = {}
c_factor = {}

for i in range(len(plant_name)):
    power[plant_name[i]] = plant_capacity[i]
    cap_cost[plant_name[i]] = capital_cost[i]
    O_M[plant_name[i]] = O_M_cost[i]
    fuel_price[plant_name[i]] = fuel_cost[i]
    c_factor[plant_name[i]] = carbon_factor[i]

# calculate marginal costs of energy supply units
MC = {}                     # marginal costs in EUR/MWh
LCOE = {}                   # LCOE in EUR/MWh
emissions = {}              # emissions in tCO2/MWh
for n in plant_name:
    MC[n] = fuel_price[n] + c_factor[n] * c_CO2
    LCOE[n] = cap_cost[n] + O_M[n] + fuel_price[n] + c_factor[n] * c_CO2
    emissions[n] = c_factor[n]



#----------------LOADING INPUT DATA for DEMAND, WIND and SOLAR-----------------
# load input data
df = pd.read_excel('Input.xlsx')
load = df['demand '+modeled_country+' actual [MW]']
PV = df['generation '+modeled_country+' solar [MW]']
Wind = df['generation '+modeled_country+' wind [MW]']

#modifying load data to shaved
load_shaved = []
avg=[]
k=0
for n in range(int(len(load)/24)):
    summ=0
    for i in range(24):
        summ += load[k+i]
    avg.append(summ/24)
    k += 24

k=0
for n in range(len(avg)):
    for i in range(24):
        deviation = load[k+i] - avg[n]
        if load[k+i] < avg[n]:
            load_shaved.append(avg[n] + (1-shaver) * deviation)
        if load[k+i] > avg[n]:
            load_shaved.append(avg[n] + (1-shaver) * deviation)
    k+=24
load = load_shaved


#modifying load data to growing


#----------------CREATING PYOMO MODEL------------------------------------------
model = ConcreteModel()
model.J = range(T-1)
model.K = range(T)
model.x = Var(plant_name, timesteps, within=NonNegativeReals)

model.P_pump = Var(timesteps, within=NonNegativeReals, bounds=(0,0.03*(SOC_max_hydro)
+ SOC_max_EV * EV_to_grid), initialize=0)
model.P_turb = Var(timesteps, within=NonNegativeReals, bounds=(0,0.03*(SOC_max_hydro)
+ SOC_max_EV * EV_to_grid), initialize=0)
model.g_c = Var(timesteps, within=NonNegativeReals, bounds=(0,transp_fraction),
initialize=0)
model.g_dc = Var(timesteps, within=NonNegativeReals, bounds=(0,transp_fraction),
initialize=0)
model.SOC = Var(timesteps, bounds=(0, SOC_max_hydro + SOC_max_EV * EV_to_grid),
initialize=0)


# defining objective function
```

```
obj_expr = sum(LCOE[n] * model.x[n, t] for n in plant_name for t in timesteps)
model.obj = Objective(expr=obj_expr,
                      sense=minimize)


# defining constraints
def SOC_power_constraint_rule(model, t):
    return model.SOC[t+1] == model.SOC[t]+model.P_pump[t]*turb_efficiency-
model.P_turb[t+1]/turb_efficiency+model.g_c[t]*load[t]*battery_efficiency-
model.g_dc[t]*load[t+1]/battery_efficiency
model.SOC_con = Constraint(model.J,
                           rule=SOC_power_constraint_rule)


def SOC_end_constraint_rule(model,t):
    return model.SOC[T-1] == model.SOC[0]
model.SOCend_con = Constraint(timesteps,
                              rule = SOC_end_constraint_rule)


def power_constraint_rule(model, n, t):
    return model.x[n, t] <= power[n]

model.power_con = Constraint(plant_name,
                             timesteps,
                             rule=power_constraint_rule)


def load_constraint_rule(model, t):
    return sum(model.x[n, t] for n in plant_name) + model.P_turb[t] - model.P_pump[t]
== load[t] * (1-model.g_c[t]+model.g_dc[t])
model.load_con = Constraint(model.K,
                            rule=load_constraint_rule)


def wind_power(model, t):
    return model.x['r_wind',t] == Wind.loc[t]
model.wind_con = Constraint(timesteps,
               rule = wind_power)


def pv_power(model, t):
    return model.x['r_solar',t] == PV.loc[t]
model.pv_con = Constraint(timesteps,
               rule = pv_power)

model.dual = pyo.Suffix(direction=pyo.Suffix.IMPORT)

opt = SolverFactory('gurobi', solver_io="python")
opt_success = opt.solve(model)



#----------------------------DATA EVALUATION-----------------------------------
# model.display()

# print("Duals")
# for c in model.component_objects(pyo.Constraint, active=True):
#     print("   Constraint", c)
#     for index in c:
#         print("      ", index, model.dual[c[index]])

# get values of optimization variables
PowerThermal = pd.DataFrame(index=timesteps, columns=plant_name)
for t in timesteps:
    for n in plant_name:
        PowerThermal.loc[t, n] = model.x[n, t].value


#calculate total emssions and total costs
total_emissions = 0
total_costs = 0

for t in timesteps:
    for n in plant_name:
        total_emissions += PowerThermal.loc[t,n]*emissions[n]
        total_costs += PowerThermal.loc[t,n]*LCOE[n]
```

```
#calculate aggregated commitment of each energy type and output to excel
committed = {}

for i in range(len(plant_name)):
    summ = 0
    for t in timesteps:
        summ += PowerThermal.loc[t,plant_name[i]]

    committed[plant_name[i]] = summ

df_output_committed = pd.DataFrame(data=committed, index=[0])
df_output_committed = (df_output_committed.T)

df_output_committed.to_excel('output_commitment.xlsx')


#get values for SOC for plotting
SOC_df = pd.DataFrame(index=timesteps, columns = ['SOC'])
for t in timesteps:
    SOC_df.loc[t] = model.SOC[t].value
# PowerThermal= pd.concat([PowerThermal, SOC_df], axis=1)
# plant_name.append('SOC')

print("Total emissions =", total_emissions)
print("Total costs =", total_costs)
```