On the Importance of Accurate Demand Representation in Large Scale Energy System Models: Hourly Profiles and Socio-Economic Dynamics

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Kurzfassung: Energy system models are large-scale representations of real-world systems that rely heavily on mathematical optimization techniques to represent the interactions between the components of a system and are widely used as tools in the decision- and policymaking processes; however, they do not come without their limitations, as the current changes and trends in power systems have shown. On the one hand, energy system models require certainty concerning their input parameters or at least clearly defined statistical properties, and they are affected by the curse of dimensionality when more detailed representations are required, as is the case when representing variable renewable energy sources. In this work, we highlight how the uncertainty about the input parameters, particularly demand, leads to significant changes in the results obtained from the models; we use an in-house bi-hourly model of the Austrian power system and show how even a slight reduction in demand, because of an energy saving policy from example, or a shift in the patterns of consumption, due to increased adoption of electric vehicles, lead to different investment and operational decisions.

Keywords: energy system models, electricity demand, energy efficiency

1 Introduction

Energy system models -ESM- serve as planning tools that allow policymakers to formulate efficient regulations for the long term. Since their inception in the seventies, they have heavily relied on mathematical optimization techniques (i.e., linear programming) to represent the interactions between the different parts of a system. Even today, these models remain essential tools for strategic insight [1].

As with any model, an ESM relies on assumptions to simplify the complexities of the real world, and as the energy systems they represent have evolved, so have ESMs and the assumptions used by researchers to build them. An example of this is the change in industry structure; ESMs from the late 1970s to early 1990s assumed a vertically integrated utility that managed the whole production chain of a system, but because of market liberalization in the early 1990s, researchers started to incorporate microeconomic aspects (i.e., profit maximation of individual agents) to model strategic behavior. Nowadays, we are in the middle of another significant shift in the energy sector due to climate change and the rulings of several countries that aim to reduce (or even put an end to) greenhouse gas emissions in the next two to three decades through the massive deployment of variable renewable energy sources -VRES-, among other options. To account for this push towards renewable energy, researchers have had to integrate the complications of VRES into ESMs. One of the primary changes in this regard is the increased detail in modeling the time dimension as we transition from monthly or weekly models towards hourly or sub-hourly ones.

Despite the increased detail in the representation of the supply due to the increasing share of VRES, among other technologies, in energy systems, demand has been pushed into the background in the ESMs landscape, and most of the models have not changed their assumptions concerning consumers' behavior; maintaining the traditional inelasticity assumption, with the exemption of some energy-intensive industries, and using simple load disaggregation techniques without analyzing the evolution of load-profiles [2]. In this work, we want to highlight the importance of analyzing the dynamics of behavioral aspects of energy demand to improve the results obtained from ESM.

Traditionally, hourly electricity consumption patterns have been related to cultural and socioeconomic aspects of a country or a state; for example, workdays may see higher power consumption during the day because of increased economic activity, such as factories and power-intensive industries operating during the daytime hours. On the other hand, weekends, such as Sundays and Saturdays, will have a different consumption pattern with spikes at different hours, reflecting the different behaviors and habits of people during these days, such as more leisure and home-based activities. This non-technical behavior of electricity consumption patterns has made them often overlooked in ESM, and, usually, they are considered just an additional parameter that stays fixed during the whole planning horizon.

Rapid changes in the environment, technological advances around mobility, heating, and renewable energies, government policies regarding the sustainability and regulation of climate change, shifts in demographics, the flexibility of energy markets as well as the tendency to avoid reliance on imported energy sources suggest that policymakers and researchers should consider multiple sources for demand data and evaluate different scenarios, with the added challenge that they should now consider the changes in the hourly patterns of electricity consumption in their analysis.

One typical example where consumption patterns change drastically for a household is related to electric vehicles -EV-; the adoption of EV has the potential to disrupt electricity demand if planners and operators do not adequately consider its impact; for example, in a recent study in Phoenix, USA [3]; showed that household electricity consumption increased significantly after EV adoption, and, between hours 20 and 05, it doubled. The authors also showed that a co-adoption of EV and photovoltaic panels -PV- led to an overall decrease in electricity consumption. In another study [4], more technical aspects concerning the integration of Low Carbon Technologies -LCT- were analyzed; their results suggest that during winter, the grids will be stressed the most due to changes in electricity demand. Unfortunately, these aspects of electricity demand modeling are often overlooked in large-scale ESM, leading to an increased model risk. This work presents our work in progress using more detailed representations of electricity demand and how model solutions change. The remainder of this paper is organized as follows: in Section 2, we present the methodology we used, then in Section 3, we describe the main results, and Section 4 contains our conclusions.

2 Methodology

This work aims to illustrate the importance of detailed modeling concerning electricity demand while running large-scale ESM. These models provide stakeholders with insight into power systems' evolution and help design policies to steer a system toward a desired goal. In our analyses, we use the model and results obtained from the work in the MILES project [5], where a full-year model with two-hour time steps was developed. In MILES, the goal was to analyze which would be an adequate mix of technologies and storage capacity for the Austrian power system in the year 2030; then, using this as a base case, we proceed to evaluate different scenarios for demand modeling and compare the decisions and results suggested by the model; in this work, we will consider two scenarios, first, an energy saving setting, and second, a redistribution of patterns in energy consumption due to an increased share of EV. As we will see, these two scenarios represent minor alterations to the overall demand but lead to noticeable changes in the investment and operational decisions.

2.1 Energy saving measures

Using those results as a starting point, we decided to run an operational problem using the investment decisions from MILES as given; then, we reduced, by 5%, the electricity demand of 10% of the hours with the highest demand, similar to the energy saving scheme suggested by the European Commission at the end of 2022 [6], and compare both solutions, both in economic and operational terms.

2.2 Adoption of electric vehicles

In the MILES model, the influence of EV on the aggregate demand is already taken into account, as the model is aligned with Austria's environmental targets; however, having an estimate of EV's share for households is not straightforward, and a precise measurement goes beyond the goal of this paper; therefore we require some simplifications. Assuming that there will not be a significant change in the share of electricity demand from households, currently around 30%, we assume that, by 2030, 20% of them will have an EV, which, in turn, will alter their consumption pattern. By using 20%, we are considering the expected low penetration of EV from the Austrian Government's Master Mobility Plan [7]. Then, to that share of the demand, we apply a shift in its consumption patterns using the results from [3], increasing the consumption share in the night and lowering it during the other hours, so, for a given day, we are not changing the demand, but its distribution; after that, we compare the results with those from the base case.

3 Results

3.1 Results under energy saving measures

When we apply the demand reduction procedure to the base case, we obtain a demand that is, in total, 387 GWh lower; this reduction is distributed among the hours with the highest demand, and the change in the pattern is barely noticeable. Despite the slight reduction, the change in investment decisions and the production mix is notable, as we go from an objective function (OPEX plus CAPEX) of 2 170 MEUR to 2 139 MEUR, a reduction of 1,44% or almost three times the demand reduction. Table 1presents the change in installed capacity; here, we can see that the main changes come from the change in storage, where the model installs 75 MWh less storage capacity, even discarding any expansion at all at one of the nodes (Ternitz). These results show the importance of considering hourly dynamics, the relevance of adequate demand estimates, and the need to account for its unavoidable uncertainty, especially in long-term models.

Technology	Base Case	Energy Saving	Difference (%)
Batteries (MW)	38,79	8,68	-78%
Batteries (MWh)	92,88	17,36	-81%
Biomass (MW)	128,82	129,68	1%
Solar (MW)	15 903,00	15 649,20	-2%
Wind (MW)	5 116,88	5 116,45	0%
Obj. Function (MEUR)	2 170	2 139	-1,44%

Table 1 Energy Saving Scenario

3.2 Results considering adoption of electric vehicles

In Figure 1 , we present the change in the profile for a given day; as we can see, the change is barely noticeable; however, there are noticeable modifications in the investment decisions made by the model, as it installs 22 MWh less storage capacity, though it does not change the nodes where it should be deployed. Concerning installed capacity, the values remain similar except for PV, where it decreases 110 MW. These results, the changes in storage and PV installations, are expected, as both technologies heavily depend on intraday patterns. A summary of the results can be found in Table 2.

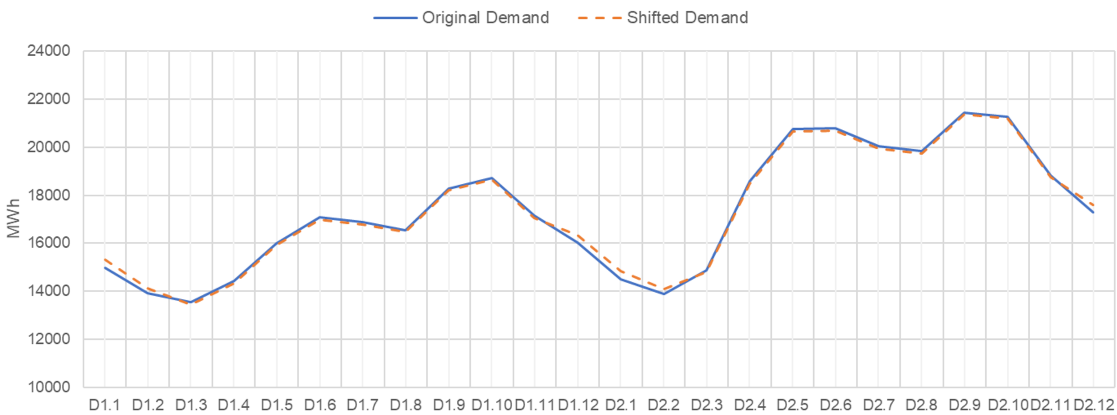

Figure 1 Demand Shift

Technology	Base Case	Energy Saving	Difference (%)
Batteries (MW)	38,79	33,56	-13,5%
Batteries (MWh)	92,88	71,69	-22,8%
Biomass (MW)	128,82	128,85	0,0%
Solar (MW)	15 903,00	15 813,00	-0,6%
Wind (MW)	5 116,88	5 117,85	0,0%
Obj. Function (MEUR)	2170,36	2168,89	-0,1%

Table 2 Demand Shift Scenario

4 Conclusions

In this work, we presented some preliminary results of our work in progress concerning the effect of changes in consumption patterns over the results of large-scale ESM; we showed that, even for small and sensible changes, the results of the models are noticeably different, particularly on technologies sensitive on intra-daily patterns, like BESS and PV. We also showed how these changes, even if logical from an energy systems perspective, do not follow a trivial relationship that can be determined ex-ante. There are multiple ways to improve these estimations, many of which require more open and secure access to anonymized data; we want to raise awareness about the importance of collaboration to have more accurate models that adequately prepare and steer our power systems toward net-zero emissions.

5 Bibliography

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