HOW WELL DO WE UNDERSTAND OUR POWER SYSTEM MODELS?

A HANDS ON EXEMPLARY ANALYSIS OF THE TIME RESOLUTION

Georgios Savvidis[1], IER – Institute of Energy Economics and Rational Energy Use, University of Stuttgart
Kai Hufendiek, IER – Institute of Energy Economics and Rational Energy Use, University of Stuttgart

1. Introduction

Over the last decades, numerous tools for analyzing and planning energy systems have been developed. They differ in many dimensions, ranging from the system boundaries, perspective, mathematical approach or even the addressed target group (Savvidis et al., 2019). Modelers typically tailor their models for every research issue they want to address in order to provide robust results with reasonable computation time. We can interpret this as a budget of model complexity – and hence computation time – which modelers try not to exceed. Some of the model features may be modeled with high details while balancing the associated high "complexity cost" with other model features in lower details.

Some of the main factors of complexity are the detail of the technological representation and the modeled time resolution. (Poncelet, Delarue, Six, Duerinck, & D'haeseleer, 2016) have shown, that those 2 categories have interdependencies which cannot be neglected during the conception phase of the technological and temporal representation in the model. This means that high technological details are better modeled together with a high time resolution. The reason for this can be described with this example: while models with low time resolution may be smaller and hence faster in terms of computation time, the absence of a high temporal resolution makes it impossible for them to capture technological details, which are only present on an hourly or sub-hourly level. In contrast, having a high temporal resolution without implementing highly detailed technology constraints may not bring any improvement to the result quality at all.

A widely used solution for this conflict of interest between time resolution and technological detail is the usage of representative time slices instead of modeling the whole period. (Collins et al 2017) show an overview of typical approaches. However, they conclude that for a sophisticated analysis of the integration of intermittent renewable energy sources, the representation of the whole time period is favorable.

Regarding power system models, (Graeber, 2002) and (vom Stein, van Bracht, Maaz, & Moser, 2017) used non-equidistant time steps in their models. In a similar fashion, the authors extended the capabilities of the European Electricity Market Model (E2M2) developed at the IER to handle non-equidistant time steps. The paper at hand will introduce a novel approach on how to make use of this time representation to better

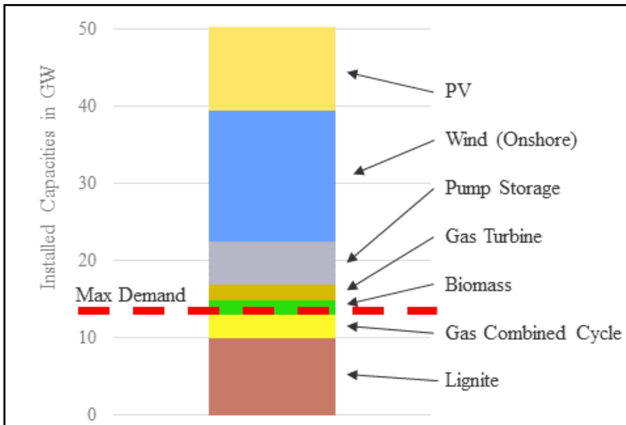
[1] E-Mail: georgios.savvidis@ier.uni-stuttgart.de
Tel-Nr.: +49 711 685 87835
Address: Institute of Energy Economics and Rational Energy Use, Hessbruehlstr. 49a, 70565 Stuttgart, Germany

understand the error mechanisms of lowering the time resolution. The results of this analysis may be used to construct smaller models with high temporal resolution, which will not be covered in this analysis. The focus lies on generating a better understanding of the impacts when lowering the time resolution.

2. Model description

E2M2 is a fundamental bottom-up linear optimization model that simultaneously calculates the cost optimal investment decisions and unit commitment. (Sun, 2013) originally developed the model and it has been continuously enriched with new features e.g. by (Steurer, 2017) and (Fleischer, in press). The authors will use the model in its "dispatch only" mode. The cost function that is subject to minimization consists of fuel costs, costs of CO_2 certificates, and variable operation and maintenance. The set of possible (unit) commitment entities consist of thermal plants aggregated by technology, curtailment of intermittent renewable units and last but not least pumping and producing capacities of storages (modeled as hydro storages). The satisfaction of electricity demand at every time step is the key restriction of the LP.

For the analysis at hand, we have parametrized the model with simplified data for the 50 Hertz region of Germany. Demand, RES production time series and thermal generation capacities for the year 2015 are taken from (ENTSO-E, 2019). We scaled the RES capacities time series to roughly match the 2030 targets of the German "Energiewende". The storage capacity has been scaled in order to depict a near future fictional scenario with more flexibility options in the system. Cost assumptions are taken from (IER - Institute of Energy Economics and Rational Energy Use, 2016). Fuel price data is derived from the internal IER database. The constructed model is realistic in its structure, but does not represent the reality. Hence, results can only be used to understand model mechanisms and are not suitable for other means. An overview of the key model aspects are shown in Figure 1.



Technology	Marginal Cost
Biomass	41,29 €
Lignite	14,84 €
Gas Combined Cycle	62,36 €
Gas Turbine	111,97 €
Storage	1,50 €
Wind Onshore	- €
PV	- €

Figure 1: Overview of model parameters

3. Time step aggregation method

Figure 2 shows the concept of static time representation, non-equidistant time representation for model size reduction and non-equidistant time representation as used for our analysis. (Graeber, 2002) and (vom Stein et al., 2017) both concluded that the challenging part of the time series, be it the electrical load or the residual load, is located at sections which inherit changes in the system. Translated to the quality of the model result, reducing the time resolution at sections with rather low gradients imposes a smaller impact on the result deviation than reducing time resolution at high gradient sections. (Savvidis & Hufendiek, 2018) have shown, that challenging parts of the residual load can be identified by 3 characteristics: at time points where the residual load of 0 MW is crossed, at time points where the residual load crosses the merit order steps or the maximum charging capacities of the storages.

Although the classification between those approaches may differ, they have one thing in common: a time series can be categorized in sections, which should be modeled in high resolution and sections where a small result deviation is expected if modeled in lower resolution. This is expressed with levels of interest in Figure 2.

For the sake of the analysis of single effects, we introduce an algorithm that aggregates time steps in an inverted fashion. This allows us to quantify the impact on the results if "interesting" section are modeled in lower resolution. Let us introduce the exemplary assumption "high gradient sections should be modeled with a high time resolution". If we do the exact opposite of this, we are able to identify the result deviation induced by the error mechanism behind the assumption. The major difference to the "model size reduction"-version of such an aggregation consists of the ability to let the rest of the time series untouched. Hence, every deviation of model behavior can be traced back to those selected time sections that have been modeled in lower resolution. This means that we intentionally provoke an error, which we then try to analyze.

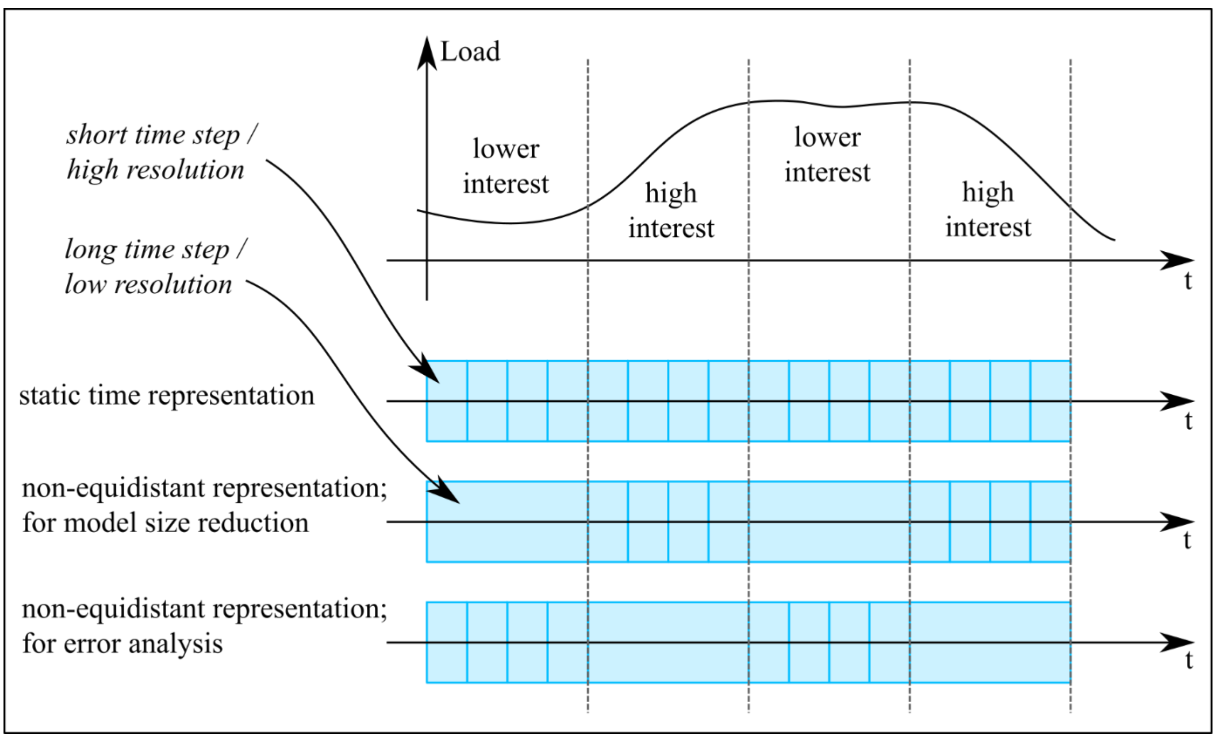


Figure 2: Concepts of time representation

4. The zero-crossing effect

Target of this analysis is the error mechanism that influences the unit commitment at time steps, where the residual load passes the value 0. This effect has been described in (Savvidis & Hufendiek, 2018) as "zero-crossing effect". It arises from the discontinuous nature of model behavior at such points in time. As long as the residual load is positive, the model needs to generate electricity. At negative residual loads, surplus energy is available for filling storages. When time is aggregated to a lower resolution at such points, information of this discontinuity is lost, as the resulting aggregated step is either positive or negative. This context is shown exemplary between an hourly (1H) and its corresponding quarter-hourly (QH) time steps in Figure 3.

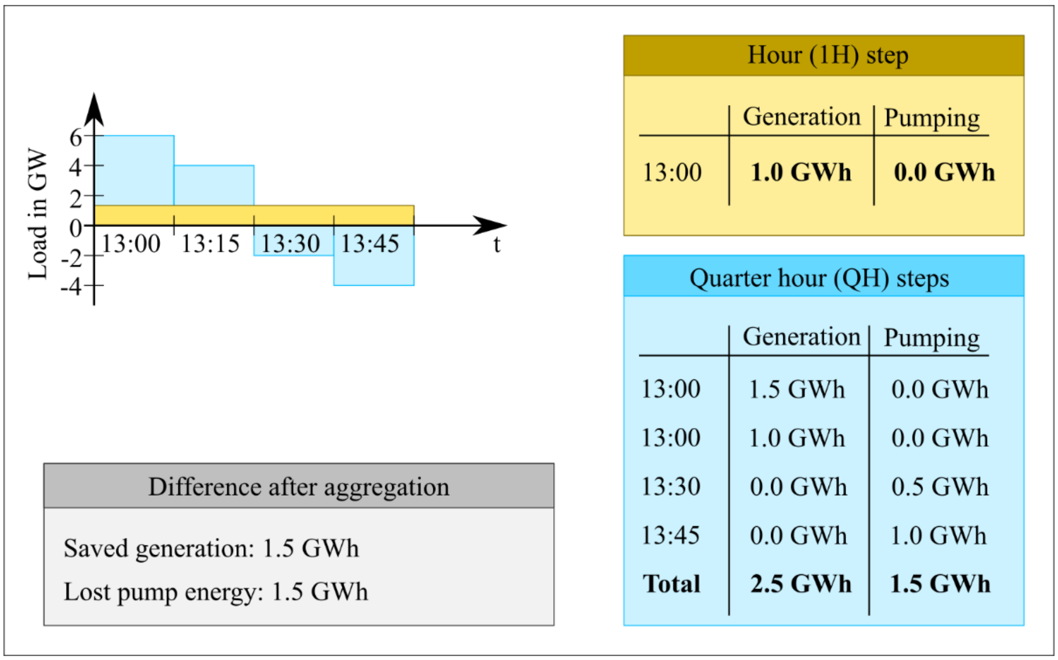


Figure 3: Explanation of the zero-crossing effect

The aggregation is done by averaging the load between the 4 QH time steps. Of course, the energy balance stays the same between the 2 variants. Nevertheless, the presence of the zero-crossing point between 13:00 and 14:00 introduces a non-linearity in the anticipated unit commitment decision. We expect the model to dispatch a thermal plant at 13:00 & 13:15 and to use the surplus energy at 13:30 & 13:45 to fill the electricity storages. This has 2 impacts on the system compared to the aggregated model version, where a thermal unit may be dispatched in its 1 time step:

- The filllevel of the storage will be different after this section
- The fuel consumption will be different in this section

Those changes in unit commitment may affect the following model results:

- Fuel consumption → generation mix, CO_2 emissions, full-load-hours of thermal production units

- Filllevel → flexibility of storage units, cycling count of storage units (ageing issues of batteries), full-load-hours of storage units

For the analysis at hand, we will use a QH resolved variable time step model (VAR), where zero-crossing time steps are aggregated to 1H resolution. This allows the exact analysis of the zero-crossing error at hourly resolved models (benchmarked against a QH resolved model). The analysis of the residual load concluded to 127 zero-crossing occasions, which are modeled at 1H resolution.

5. Error mechanism analysis

Prior to conducting model runs, we will introduce 2 metrics which grasp the error potential of aggregated time steps at zero-crossing sections. Firstly, we calculate the residual load without information on curtailment (as this would be a model result). Hourly models usually provide this information as power in MW, but here we will use energy in MWh as the reference unit. This allows a more flexible comparison between different time resolutions. Technical restrictions of power plants may still be calculated with power as reference unit, but comparability of different resolved time steps is better with energy (MWh) as the reference unit.

The residual load R(t) is calculated by subtracting the infeed profile of uncontrollable renewable (RES) units from the net electricity demand. German TSO operators provide this data at QH resolution. For the analysis at hand, we will aggregate (the zero-crossing sections) to 1H resolution to later compare them to a fully QH resolved model. We will note time steps of a QH resolved model with indices $i \in I$, of a 1H resolved model with the indices $j \in J$ and of a VAR model with $k \in K$. In addition, we define $\kappa \in Z \subset K$ which refers to all k of aggregated time steps. Further, when comparing the QH to the 1H model, every time step T_j^{1H} is associated to 4 higher resolved time steps T_i^{QH}.

Aggregating load at the dimension of energy (MWh) is done by adding up the amount of energy over all time steps i, which are subject to aggregation to a (longer) time step j. This corresponds to averaging the load at the dimension of power (MW). For our purposes, we will note the QH residual load as $R(T_i^{QH})$ with $1 \leq i \leq 35040$ and the 1H resolution $R(T_j^{1H})$ with $1 \leq j \leq 8760$. In order to construct a VAR model, a QH model is taken as a basis and at points of interest, 4 QH step can be replaced by 1 1H step from the same section of the 1H model like also done in (Savvidis & Hufendiek, 2018).

We will use 2 metrics for the analysis of the error. Both can also be observed in Figure 3. First, we introduce the saved amount of generation $E_{savedGen}^{Pot}$. It represents the amount of energy that the higher aggregated model is not forced to generate from dispatchable plants. Because other restrictions in the model might lead to a different behavior, we interpret this as ***potentially*** saved generation, which is marked with the keyword "Pot".

In order to calculate it, we will introduce the generation side of the residual load as

$$R_{Gen}(T) = \begin{cases} R(T)\ for\ all\ R(T) > 0 \\ 0\ for\ all\ R(T) \leq 0 \end{cases}$$

and the pumping side of the residual load, as

$$R_{Pump}(T) = \begin{cases} R(T)\ for\ all\ R(T) < 0 \\ 0\ for\ all\ R(T) \geq 0. \end{cases}$$

Note, that $R_{Gen}(T) + R_{Pump}(T) = R(T)$ applies. We then are able to calculate

$$E^{Pot}_{savedGen}(T^{1H}_{\kappa}) = \sum_{i} \left(R_{Gen}\left(T^{QH}_{i}\right) \right) \ - R_{Gen}(T^{1H}_{\kappa})\ ,\ \ \forall i\ which\ belong\ to\ \kappa \in Z$$

The second metric we want to introduce is $E^{Pot}_{lostSto}$ which describes the amount of energy not available for filling up the storages due to rounding effects at the zero-crossing point. This is analogous to the calculation of the saved generation:

$$E^{Pot}_{lostSto}(T^{1H}_{\kappa}) = \sum_{i} \left| R_{Pump}\left(T^{QH}_{i}\right) \right| \ - \left| R_{Pump}(T^{1H}_{\kappa}) \right|\ ,\ \ \forall i\ which\ belong\ to\ \kappa \in Z.$$

Both metrics describe the difference of the allocation of energy if the residual load is separated between its positive and negative side. This reflects the potentially different dispatch decision that the optimization model may consider at a zero-crossing point between thermal generation and storing energy. Due to the fact that energy is not lost at the aggregation process, both metrics have the same value.

The analysis of the residual load for the model described in section 2 resulted in:

$$\sum_{\kappa \in Z} E^{Pot}_{lostSto}(T^{1H}_{\kappa}) = \sum_{\kappa \in Z} E^{Pot}_{savedGen}(T^{1H}_{\kappa}) = 15\ GWh$$

This value represents the maximum amount of energy that is potentially not used by storages and hence, will be distributed differently in the system. This is roughly 2 times the storage content of the modeled storages.

For the further analysis of the zero-crossing effect we will compare the results of the VAR model to the results of a QH model. All differences in the results are directly linked to the zero-crossing error, which we provoked. We are now able to trace the deviating model behavior caused by $E^{Pot}_{lostSto}$ and $E^{Pot}_{savedGen}$. The first thing to look for is how much of the potentially lost pumped energy is actually lost, which we can calculate as

$$E_{lostSto} = \sum_{all\ i \in I} E_{pump}\left(T^{QH}_{i}\right) - \sum_{all\ k \in K} E_{pump}\left(T^{VAR}_{k}\right).$$

with $E_{pump}(T)$ … Amount of energy pumped (stored) into the storage unit at time step T.

All energy which is not available to the storages needs to be replaced by other means in the model. There are 3 options for the model:

- Directly replacing the lost energy through other power plants at later points in time without the usage of storage units (storage losses caused by inefficiencies do not occur with this option) → $E_{stoRepl,dir}$

- Indirectly replacing the missing amount by filling up storages with electricity generated from thermal units e.g. at time points where low cost units are available (this will probably be less often, because it is associated with higher costs) → $E_{stoRepl,indir}$
- Fill the storage at later time points with available energy from RES which would be curtailed at QH resolution due to full storages. (Storages have more free space due to $E_{lostSto}$.)

All options can be quantified with the calculated model results. Firstly, we need to determine the amount of energy loaded into storages that originated from thermal power plants. This is done by:

$$E_{pump,therm}(T_i) = \begin{cases} \min\left[E_{pump,max}, E_{therm}(T_i)\right], for\ i | E_{pump}(T_i) > 0 \wedge E_{therm}(T_i) > 0 \\ 0, for\ all\ other\ cases \end{cases}$$

with $E_{therm}(T_i)$ … the amount of electricity generated by all thermal plants at time step T_i

$E_{pump,max}$ … maximum pumping capacity of (aggregated) storage unit

This translates into: "if the system is loading the storages and thermal units generate at this moment, then it is assumed, that they load up the storages (otherwise they would not generate electricity as the system has enough available at this moment). If this is the case, then all energy up to the loading maximum of storages is accounted to $E_{sto,therm}$."

The indirect replacement of energy via filling up storages can be calculated as

$$E_{stoRepl,indir} = \left| \sum_k E_{pump,therm}\left(T_k^{VAR}\right) - \sum_i E_{pump,therm}\left(T_i^{QH}\right) \right|$$

The difference of amounts of energy originating from thermal units equals the indirect energy compensation for lost pumped energy.

The direct replacement is calculated in a similar way. It can be quantified by the difference in electricity generation from storages, because electricity not originating from storages are replaced by other means. The calculation is:

$$E_{stoRepl,dir} = \left| \sum_k E_{sto}\left(T_k^{VAR}\right) - \sum_i E_{Sto}\left(T_i^{QH}\right) \right|$$

with $E_{sto}(T_i)$ … amount of electricity generated from storage units at time step T_i.

We can use this information to trace the lost and saved amounts of energy on the negative and positive side of the residual load.

6. Results

The results of the 2 conducted runs (VAR and QH) show, that at the VAR model, storages contribute 8 GWh more electricity to the system while 3 GWh of electricity are provided less by thermal power plants. This shows that aggregation at zero-crossing sections leads to overestimation of the contribution of RES as well as underestimation of the flexibility demand. However, the total error of storage dispatch between the models is 1.2%, which is rather low. But as stated above, if modelers can estimate this error prior to a model run, trustworthiness of model results will be better.

The measured deviation can be traced back to the zero-crossing effect, as this is the only provoked error in the model. It manifests as roughly 20% of the identified maximum error. Figure 4 shows the result of the further analysis. The upper part of the y-axis represents the pumping side of the residual load and the lower part the generation side. On the left, $E_{lostSto}^{Pot}$ and $E_{savedGen}^{Pot}$ are drawn. They represent the maximum error induced by the aggregation of zero-crossing time steps from QH to 1H resolution. They can be calculated prior to a model run, which makes them a good indicator on how high the error impact might be (see section 5).

The right side of the figure shows all insights generated with the comparison of the VAR model to the QH model. We can observe that roughly 2/3 of the potentially lost pump energy is actually lost. The results show, that this amount of electricity (after storage losses) is directly replaced by thermal generation at later points in time.

About 1/4 of the potentially lost pumped energy is still being pumped. Not from RES, but from thermal plants. The optimizer tries to utilize the additionally available storage for avoiding high cost thermal units. Therefore, if possible at low-load time steps, it uses low cost thermal plants to fill the additionally available storage. This might be more expensive in comparison to the QH resolved run where this energy originates from cheap RES, but it is the next cheapest approach if this energy is not available due to the zero-crossing effect.

The rest of the potentially lost pumped energy results in curtailment differences. Because storage fill levels tend to be lower in the aggregated model, more electricity from RES can be utilized.

Figure 4 shows clearly, that the deviation is caused by the "not lost" storage losses and the not curtailed RES energy. Every dispatch difference between the VAR and the QH model can be summed up with those 2 parameters. They are drawn at the right end of the figure and marked with "zero-crossing error". The difference in thermal power plant dispatch matches exactly those 2 parameters. Changes in fuel usage, CO2 emissions, variable costs and other model aspects are present and directly linked to the energy amounts depicted in Figure 4.

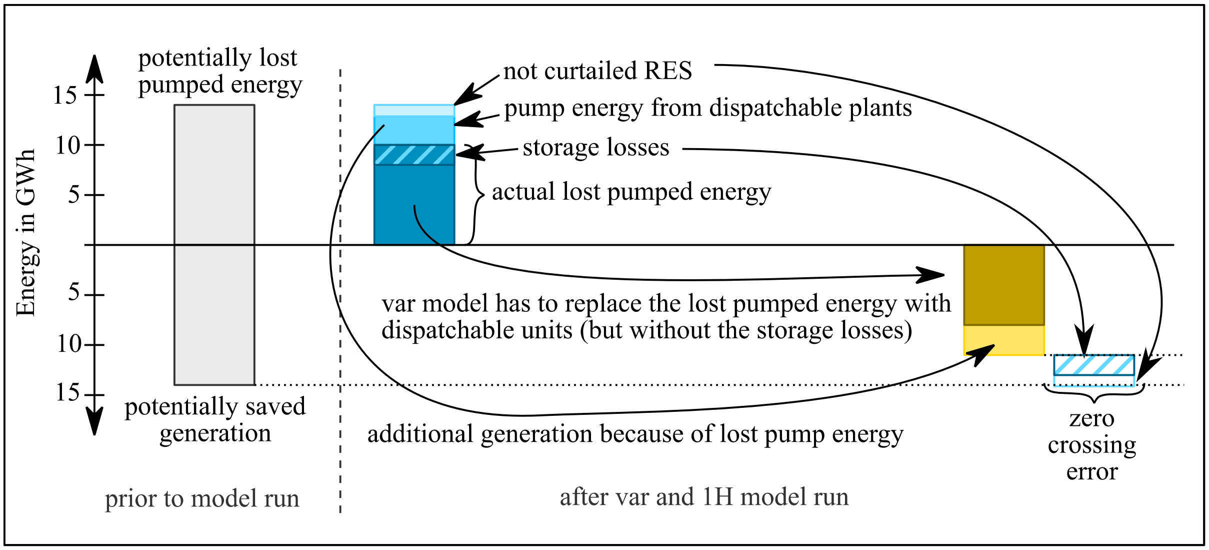


Figure 4: Detailed analysis of the zero-crossing error mechanic

The above-described approach may help modelers to better estimate the impact of their time resolution choice. The results from the VAR model represent the zero-crossing error for 1H models. They can estimate the maximum potential error caused by the zero-crossing effect by calculating either , $E^{Pot}_{lostSto}$ or $E^{Pot}_{savedGen}$. A good guess on the actual error can be done by calculating the potential storage losses of $E^{Pot}_{lostSto}$. The data needs are: time series of demand and renewable infeed and average storage efficiency of available storage units. With this, modelers can calculate $E^{Pot}_{lostSto}$ and multiply it with the storage efficiency.

This highlights the key role of storage technologies on the error mechanism. We expect higher error in systems with low-efficiency-storages. This is especially important when modelers try to find optimal future electricity sector configurations as rising shares of RES are often accompanied with storage investments. A scenario with high e-mobility and strong focus on PV will probably be accompanied with high shares of Li-Ion batteries, as they are commonly used for electric vehicles and residential PV batteries. Because such batteries comprise a lower efficiency than hydro storages, a high time resolution around zero-crossing points may be of a much higher importance. In contrast, a scenario at Scandinavian countries with lots of opportunities for pumped hydro storages with high efficiencies, may be lesser impact by this effect. This would apply even if we have the same amount of storages and the same thermal power plants in both scenarios.

7. Summary and Outlook

Rising complexity of power system models and new challenges of future electricity sector configurations impose hard challenges on energy and electricity system modelers. There is a high need in reducing computation time on the one hand, but on the other hand the effects of such simplifications are difficult to foresee. We propose the usage of variable aggregated time steps, not for model size reduction, but for generating deeper understanding of effects induced by model simplifications. The focus is set on the reduction of time resolution in general and on the zero-crossing effect described in (Savvidis and Hufendiek 2018) in particular.

In this analysis, we isolated the zero-crossing effect and described metrics:

a. to estimate the error potential prior to a model run, if critical (prior determinable) time steps are aggregated and
b. to track the imposed errors through the model results and identify its implications

Although the error is not high for the time resolution used in this analysis, knowledge on model behavior is generated. This might help modelers to better tailor their models to their specific problems, in order to minimize computation time and to enhance their result quality.

We identified that the main driver for result deviation is driven by the technological characteristics of storages. In particular, their efficiency and storage capacity. We also proposed a method on how to estimate the maximum error caused by the zero-crossing effect.

Analogous to the procedure used in this analysis, further effects, such as “peak shaving effect” and “merit order effect” described in (Savvidis & Hufendiek, 2018) or other effects like ramping effects addressed in (vom Stein et al., 2017) may be analyzed. In addition, activating the investment module of E2M2 in further analyses could help identifying the impact on investment results of the analyzed error mechanism.

The authors pledge, that modelers should intensively work on identifying the error mechanisms in their models. Providing indicators of potential model errors significantly helps in the correct interpretation of the model results and enhances their trustworthiness.

8. Acknowledgments

The authors acknowledge the financial support by the Federal Ministry for Economic Affairs and Energy of Germany (BMWi) in the project “4NEMO - Research Network for the Development of New Methods in Energysystem Modeling; research project: 0324008A”.

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