Constructing aggregated time series data for energy system model analyses

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Abstract

With application of energy system models one of the challenges is to achieve an appropriate balance between the number of time segments (for example, hours) in the model, the effort in solving the model and the quality of the model results. This challenge is getting more intense with increased amounts and sources of variable renewable energy, because time series for such sources display characteristics that are distinctly different from one another and from those of electricity and heat demand.

This paper presents a new method for aggregating time series for energy system analyses. The method is applied to a large scale energy system model to illustrate and validate the developed method.

The paper discusses criteria that may be relevant for the evaluation of the quality of a given time aggregation. This depends on the composition of the energy system in question as well as the focus of any given project. Relevant project foci include investments in renewable energy, support mechanisms, electricity prices, the role of flexibility on demand vs supply sides, transmission and bottlenecks, and emissions.

The proposed method was applied to the large-scale Balmorel energy system model with data representative of the Nordic energy system. A selection of countries was chosen to feature different challenges in power market modelling. The original input time series are given on hourly basis for a full year, while aggregated time series with various aggregation resolutions down to almost 1% of the original are constructed and applied. The changes in dynamics in both the seasonal and short-term perspective are observed for various output variables.

The key finding of the paper is that although the chosen aggregation technique was generally successful in regards of reduction of solution time and also for the accuracy of some of the results, attention should be given to choosing the aggregation strategy according to the investigated task at hand. Results indicate that electricity prices and fuel use (and thus also emissions) are fairly robust to aggregation in the levels tested, while investments are more sensitive.

Keywords: Energy system models, time series, aggregation, renewable integration

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1. Introduction

Weaning of fossil fuels is a common target for the future. Most strategies, achieving this target, are based on increasing shares of **V**ariable **R**enewable **E**nergy (VRE), which magnifies the need for optimal flexibility modelling in the energy models. To study flexibility needs, long-term **I**nvestment **M**odels (IMs) are used, which often span 20-40 years [1]. To secure a more accurate modelling of the capacities needed for a stable daily energy flow, IMs are often combined with a short-term Dispatch Model, which has the purpose of planning the daily energy flow, where the analyzed period span from days to years [1]. Apart from the increased complexity caused by the size of a combined long- and a short-term model, the combination also complicates the task of finding a common timescale fulfilling both model purposes. In this paper, the Balmorel model [2], will be used. Apart from being a combined planning and investment model for electricity and district heat, it is also a large-scale model with the possibility of spanning multiple countries which increases the complexity even further. With this high level of complexity, simplification techniques are required.

Time aggregation has shown to be a valuable technique to simplify complex energy models. The idea is to define a similarity measure and then replace similar hours with a suitably weighted representative in the input data. Some shortcomings have been observed in some methods. In particular, when modelling increased shares of VRE, the need of flexibility may be underestimated. The major challenges are to find a time resolution securing base-load capacity, and overproduction of VRE to be handled effectively [3].

This paper provides a strategy to find an aggregated time resolution, which sufficiently captures the variability in demand and supply. The strategy is based on a selection of historical data as starting point, followed by a modification. The selection should be representative of the system modelled. The modification aims at representing key characteristics of this, including extreme values, duration curves of values and ramping, and chronology. Modifying the selected historical data differentiates our technique from many of the techniques in the literature, as well as the fact that we provide a validation of the aggregation both according to data replication and to the quality of the model with reduced complexity.

Section 2 provides a literature review of aggregation techniques, while section 3 accounts for the methodology and our aggregation suggestion together with validation and a discussion of the results. Finally, section 4 concludes the topic with discussion.

The applied aggregation code will become available under open source condition at the Balmorel home page. [2] [4]

2. Literature overview

There tends to be a dominance of time aggregation techniques based on **H**euristic **S**election (HS). The idea is to identify typical behavior of the original time series, and select time segments representing these different behaviors. Often this consists of selecting historical weeks, days or hours according to seasonality, weekend/workday, night/day and peak/off-peak deviations. Examples are

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listed in [5]. Such aggregation have shown to capture the variability in demand well, but since the same systematic behaviors are not seen in historical wind data, the techniques now tend to smooth the variability of renewable sources [6], and one consequence is under-estimation of the flexibility needs. As pointed out in [7], the real challenge lies in representing the variability of wind, solar and demand in combination. Adapting to this, the HS approaches are modified with the aim of focusing more on the extreme cases of the variability. This is achieved by securing low, medium and high VRE supply regimes, securing the capturing of different correlations between demand and supply [8], or selecting the most variable wind profile for each day type (working day or holiday) of each season [9]. Aggregation techniques based on cluster analysis (CA) do not suffer as much with increasing VRE shares [1] [10], since these are less based on pre-expected seasonalities in the data. The idea is to group elements such that the difference between clusters is maximized while the difference within each group is minimized. Due to the technical features of CA, variability can be better captured than with HS, but chronology on the other hand is disregarded.

In general, for the time segments to capture the variability of both demand and VRE, [5] identifies 3 properties that the time segments should reflect; 1) Annual electricity demand and average VRE capacity factors for each region, 2) The region specific load duration curves for electricity demand and VRE technologies and 3) Spatial and temporal correlation of electricity demand and VRE electricity infeed. This has caused especially the **R**esidual **L**oad **D**uration **C**urve (RLDC) to be a popular validation measure [1], for aggregation techniques. According to [11], using a time resolution with a too flat RCLD approximation, causes over- and underproduction of VRE to be underestimated. Consequently, the solutions will not reflect the need of technologies handling shut-downs or the need of storage or back-up productions. To secure the best approximation of RLDC, an idea is to use the similarity in RLDC to select the time segments, instead of only using it as a post-validation as typically done in the HS and CA based aggregations. This idea is seen in [12], where an exhaustive search is used to find the selection of historical weeks minimizing the sum of squared error between the original RLDC and the approximated.

A slightly different approach is seen in [13], where an optimization model is derived, selecting representative days and corresponding weights, which minimizes the deviation of the **D**uration **C**urves (DC) of load, wind and PV of the selected days from the original DCs. A drawback of time aggregation approaches using optimization is that it is rather time consuming to find the selection and requires an implementation effort.

Also, only validating an aggregation on the ability to replicate the RLDC is, by [11], considered risky since a good approximation of RLDC does not secure a good representation of the demand, wind and PV curves due to the RLDC not containing information about correlation between the individual profiles. This causes [13] to make an extension to their suggested optimization approach, where a **C**orrelation **D**uration **C**urve (CDC) for each aggregated time series are approximated as well. An example of a CA technique accounting for hour-to-hour changes in demand are suggested in [14]. The major drawback of using duration curves in optimization based time aggregation, is the loss of chronology causing that short-term storages, unit commitment and ramping constraints cannot be modelled ([13],[5]).

According to [5], despite the huge amount of different aggregation approaches, they all have certain shortcomings. Most of the aggregations do not reduce the computational complexity of large investment models enough. Others have a too narrow focus by only considering one VRE time series, one region or disregard spatial compositions of feed-in levels. Furthermore the literature lacks validation and comparison of the different aggregations [9].

3. Aggregation methodology and validation

3.1. Methodology of aggregation

The method constructs new time series that are approximations to the original series but with less time segments. The construction secures that the minimum, maximum and average values are the same in the aggregated as in the original series. These three characteristics are classical within the energy system analysis where for some period of time the average value translates to total energy and minimum and maximum characterize the span of power values over that period. The extreme values are of importance for system adequacy (lack of capacity, in particular).

The duration curve of the load time series is relevant for the distribution of the generation on different types of generation technologies (distinguished e.g. whether they are base, middle and low peak load units, by the type of fuel used, by their operating characteristic like ramping limitations, marginal costs, or otherwise), and hence also for the distribution of marginal costs and hence e.g. electricity prices. With non-dispathcable VRE it is rather the residual non-dispatchable load curve that are relevant for these consequences.

Flexibility, expressed e.g. as capabilities of ramping (i.e., the difference between time series' values in two consecutive time segments) or storage capacities is becoming increasingly in focus with increased amounts of renewable variable energy, because ramping and storage may be seen as indicators related to flexibility. For instance, with increased wind generated energy in an energy system, the associated ramping of wind power will increase, with implications for the requirement to dispatchable units and flexible demand in the system. As with the values of the time series, the minimum, maximum and average ramping of the series are relevant.

Also chronology is to be considered. A distinction will here be made between chronology of power and chronology of energy. Chronology of power is of importance mainly for variations over shorter time intervals. The above mentioned ramping relating two consecutive hours is an example, while also intervals of three hours or maybe more might be relevant. For much longer intervals, e.g over several weeks, chronology of energy is relevant. An example is large hydro storage installations that distribute hydro inflow over a year or maybe between years. Depending on seasonality of inflow and generation as well as storage capacity it may be important to have a good representation of the seasonality in the aggregated inflow. Similar considerations may be relevant for e.g. gas storage. A an example of chronology of energy within a shorter interval is heating of residential houses, where supply from e.g. electricity may be switched off, but allowed duration of the switch-off is related to the thermal dynamics of the house and requirements for comfort.

Based on these observations the developed method will construct an aggregated time series from a given time series in full annual hourly resolution such that compared to the original one it

- Preserves minimum, maximum and average values
- Preserves minimum and maximum ramping

- Approximates duration curves for values and for ramping
- Approximates chronology

It is not possible to have identical duration curves because the number of time segments differ between the original and the aggregated time series. However, this may be circumvented as follows. For example, if the 672 hours of four weeks are to be aggregated to 168 hours in one week the value for every fourth hour of the 672 are taken and each one related to the value in the corresponding hour of the 168 in the aggregated week. Then a closeness measure may be defined, the one used here is the sum of squared difference between all such pairs of hours.

It is in general not possible or at least unlikely to have best approximations for value and ramping duration curves simultaneously, nor to have any of these simultaneous with best chronology these objectives.

The above aims to hold for any of the time series in a given energy system model, including electricity and heat demand series, and renewable electricity generation, such as wind, solar and hydro power (storable and run-of-river). For models with spatial representation the aggregated time series have the same spatial representation (i.e., there is no spatial aggregation).

The challenges of correlation in time and space implied by the handling of different types of time series, all of them with spatial differentiation, are many-sided. For instance, correlation between electricity and heat demand has importance for the operation of district heating, and correlation between wind and solar induced electricity generation is important for the operation of the dispatchable generation units. Spatial differentiation has implication for e.g. correlation of wind power generation and transmission of electricity between countries.

In the study presented here, correlation is managed by selecting the same time period over all time series' types and spatial locations. More specifically, the handling of chronology is based on residual electricity load time series for all the geographical entities together.

As seen, the philosophy of the present method is in essence one of *construction* of new time series with specified relations to the original ones. An example how four weeks have been aggregated into a single one can be observed in Figure 1.

3.2. Method of testing and validating aggregated time series

In order to validate the aggregation strategy described above, five aggregated profiles representing the full year were created and used for testing. The profiles are represented by deterministic values and differ from one another according to how much they represent the seasonal variation and the hourly fluctuations.

The test cases presented here are based on the handling of time in the Balmorel model [2]. Here, the year is divided into a number of Seasons, and each Season is further subdivided into Terms. From a total of 52 distinct Seasons and 168 Terms in each, the following aggregation levels were tested in the model:

- S52-T168 - 52 Seasons and 168 Terms in each Season (full resolution of 8736 individual time segments)
- S13-T168 - 13 Seasons and 168 Terms in each Season (2184 individual time segments)

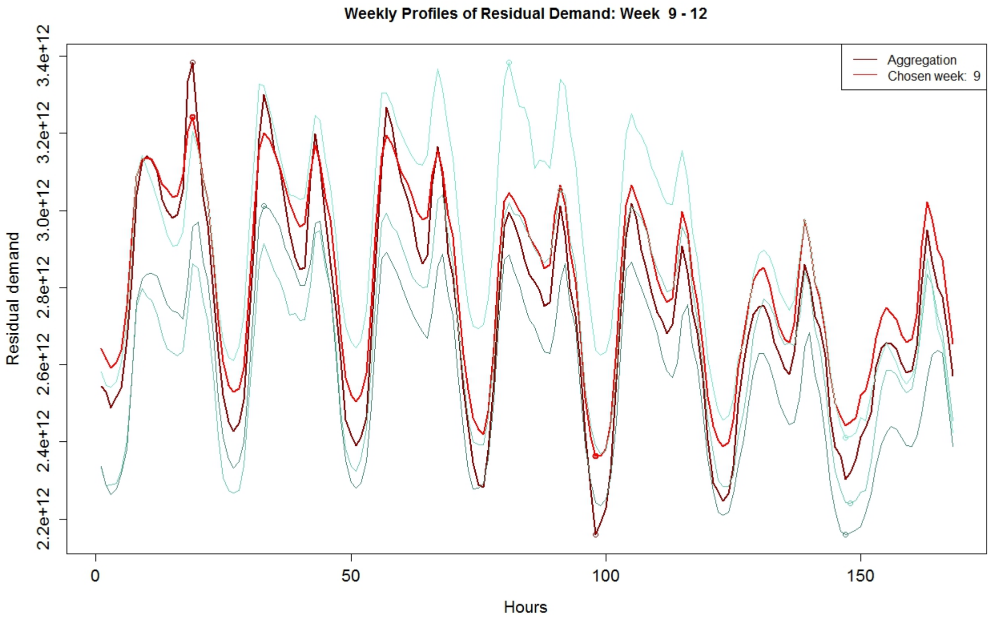

Figure 1: The choice and alteration of a single week from a selection of four

- S13-T056 - 13 Seasons and 56 Terms in each Season (728 individual time segments)
- S04-T168 - 4 Seasons and 168 Terms in each Season (672 individual time segments)
- S13-T024 - 13 Seasons and 24 Terms in each Season (312 individual time segments)
- S04-T024 - 4 Seasons and 24 Terms in each Season (96 individual time segments)

It can be seen that for the purpose of the analysis, the time resolution of the annual time series is reduced by a factor which lies between 4 and 91. In order to asses the impact of aggregation in the modelling context, and compare the effects of different aggregation strategies, an energy system model was set up. The particular model chosen was Balmorel. Balmorel is a deterministic partial equilibrium optimization model in GAMS, which includes the power and district heating sectors in the simulation; in this paper, only linear modelling parts of the model were applied [4]. The particular data set up in the model was to represent a well-balanced mix of fuels along with an uneven geographical distribution of the fuels (inspired by the Nordic and Baltic countries). The overall fuel mix is chosen such that from overall power production, in round numbers 40% was provided by hydro power plants, 25% from nuclear, 10% from wind and 25% from thermal power plants (natural gas, coal and biomass etc). In the model, specific regions can be observed which are dominated by hydro, wind or thermal power plants such that congestion in transmission capacities can also be observed between those regions. Testing of the aggregated time series was done by comparison of model results. The model was run with a full time resolution and then in the aggregated format, where all the time series had been replaced by their aggregated versions, as described above.

Three cases were developed in the model in order to investigate the impact of the different aggregation strategies:

- Power dispatch
- Power dispatch with investments possible in new wind turbine and gas turbine capacities ("Dispatch+W+G")
- Power dispatch with investments possible in new wind turbine and electricity storage capacities ("Dispatch+W+Sto")

In the cases with investment possibilities, the power demand was increased to motivate the entry of new capacity. The chosen cases aim to give an overview of the fundamental challenges in aggregation as well as indicate whether aggregating in a model can have a significant distorting effect on the competitiveness and utilization of different technologies in a power system.

3.3. Model results

As expected, the time spent to solving optimization time was cut significantly by reducing the level of temporal detail in the model. The solver execution time is shown in Table 1. However, the case with dispatch and investments in wind turbines and electricity storage, could not be solved for full resolution at all. The optimization ran for 72 hours without reaching the optimal solution and was then terminated due to hardware limitations at hand. This illustrates the drastically increasing complexity in the model when the number of modelled time segments increases along with possibility of storage, which increases the relations between time segments further.

Table 1: Optimization time using different time resolution (seconds)

Studied case	**Full resolution**	**S13-T168**	**S13-T056**	**S04-T168**	**S13-T024**	**S04-T024**
Dispatch optimization	15551	1125	135	131	33	3
Dispatch + W + G	15201	9016	766	677	151	8
Dispatch + W + Sto	N/A	46647	5280	5715	642	27

From modelling results several observations are noted. Firstly, the model results were quite indifferent throughout the aggregation strategies in regards of annual fuel consumption in the system. The changes of market share of any fuel remained below 0.1 %. Therefore, the results are also quite indifferent in regards to emission amounts. The annual average power market price was observed to be quite similar across aggregation techniques in the three studied cases as well. The prices are indicated in Figure 2. Note that as previously mentioned the data differ between the three cases by having having increased demand in the two investments cases; hence, the price levels are not comparable between cases. Similarly, the price levels in the investment cases include marginal investment costs.

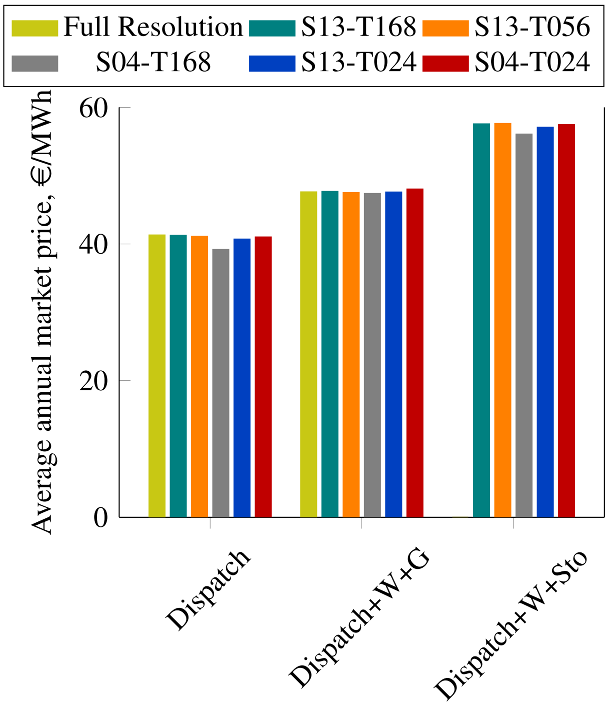

Figure 2: Averages of hourly electricity market prices in analysed scenarios

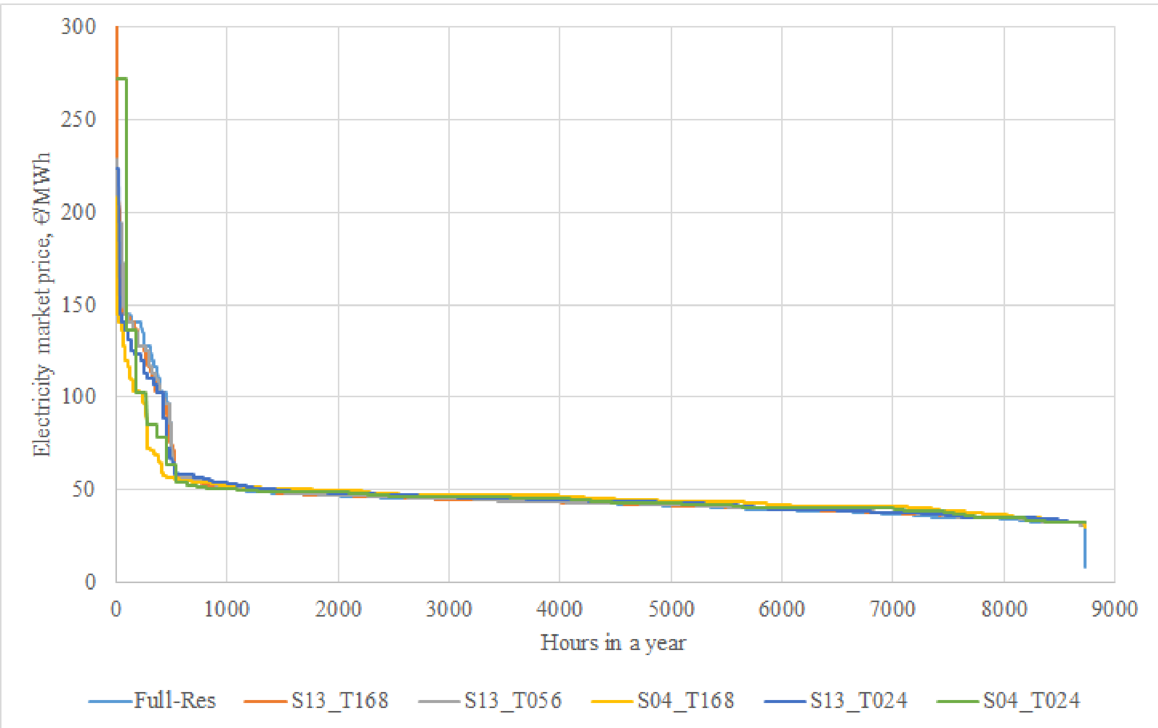

Figure 3: Electricty market price duration curves in Dispatch+W+G case between the aggregation strategies. Note: in the full resolution model the peak price is 3088 €/MWh, and in S13-T168 it is 1415 €/MWh, currently cropped out

A closer inspection of price duration curves in Figure 3 revealed, however, that a significant difference in the shape of the price duration curved can be observed in the case of S04-T168 and S04-T024, the aggregation strategies with the smallest level of detail in the seasonal characteristics. it can be observed than in the two named cases, the number of hours with a high market price are underestimated, and somewhat of an opposite effect can be seen in the lower price range. Another important factor is the observation of peak prices: the finer the time resolution, the higher peak price in the case of dispatch with wind and gas. However, at the same time the relative length of the peak price hour is smaller as well. This is due to the marginal cost based electricity price in the linear model: in the case of investments in new technology are necessary in order to cover peak demand, then the cost is applied to the specific time segment. However, the longer the relative length of the time segment, the lower the marginal value. The issue, however, indicates a clear signal that in addition depicting the extremes in the RLDC, it is also important to depict the correct length or weight of those extremes.

Observing the investment decisions make by the model in the cases with investments allowed, it can be seen that the level of realized investments vary as well. Investments are shown in Figure 4.

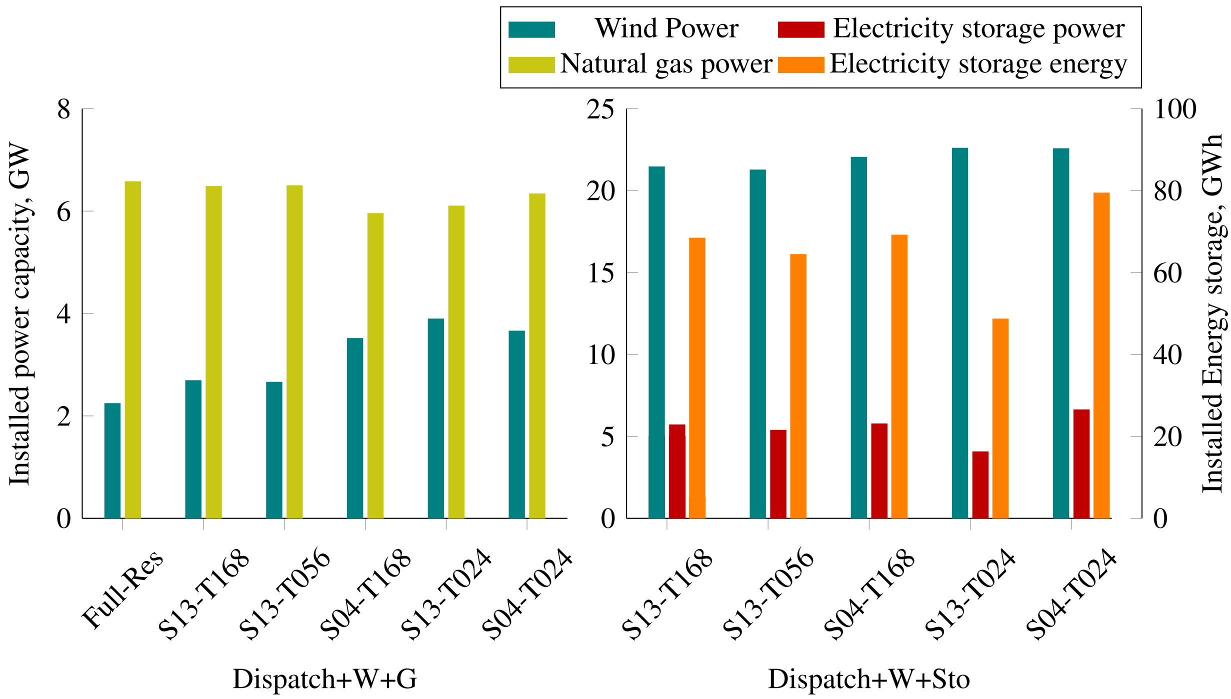

Figure 4: Endogenous investment decisions in the modelled aggregation tests

In the case with wind and natural gas investments the lowest amount of wind turbines were built in the reference run with full time resolution. Investment decisions seem to err increasingly from the reference run as the level of temporal detail decreases. Because it was not possible to solve the investment model with storage for the whole year with an hourly resolution, a perfect comparison can not be made. It is seen, however, that the amount of electricity storage seems to decrease with decreasing level of detail in the hourly resolution. Seasonal aggregation seems to have a small effect on the amount of storage.

4. Conclusion

As observed in the shown data about model test results, significantly shorter solution times can be achieved by using time aggregated input data, potentially at a the cost of providing misleading conclusions. Here, five conclusions are drawn concerning potential drawbacks.

First, reducing the level of temporal details distort the distribution of market price levels, and hence also the average prices. Second, aggregated time series seem to imply that wind turbines as more attractive for new investments in the model. In general terms this may relative competitiveness of technologies depends on the time aggregation level. Third, with decreasing level of detail in time within Seasons, the attractiveness of electricity storage decreased, illustrating again an aspect of relative competitiveness of technologies. Forth, for some technologies the distorting effect seems to derive from the general level of aggregation, while for others, the specific aggregation strategies have a larger effect. Fifth, it is more important to assess the relative length of aggregated time segments, as shown in the distortion of peak prices.

Overall it can be seen that the chosen aggregation strategy contains some drawbacks outlined in previous research in Section 2, but overall but the overall results indicate the method to be suitable for energy systems modelling.

Three open issues with implications for aggregation methodology stand out from the tests. First, a deeper understanding of the reasons for increased investments in wind with more aggressive aggregation is required in order to improve aggregation methods. Second, since substantial bottlenecks in the transmission system will partly distort chronology over space, how could chronology then be handled. Third, is it possible to give more concise indications of which type and which (maximum) level of aggregation that are relevant for given model types.

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