Flexible time aggregation for energy systems modelling

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Abstract
With high shares of renewable generation and a reliance on storage, modelling large scale energy systems is computationally challenging. One factor driving the complexity of these models is the need for a high temporal resolution over a long period; a typical baseline is modelling all 8760 hours in a year. While simple methods such as down-sampling and segmentation are effective at reducing the number of time-steps in a model, there is potential for more sophisticated simplifications. In this work, we propose a flexible time aggregation framework where individual components in the systems (e.g. generators, storage units) may be modelled at a lower time resolution. We base the method on the theory of aggregation in linear programming, giving the possibility for provable bounds on the resulting objective value. These ideas have only been explored in a limited fashion in the context of energy systems modelling, and we highlight their potential for large scale energy system models and the next steps for research.

Keywords: Energy systems modelling, optimisation, time aggregation.

Motivation
In the Paris Agreement we have set out to achieve a carbon neutral world by mid-century, necessitating a global shift to renewable energy sources. One element enabling this transition is mathematical modelling in order to explore and design future energy systems. With accurate models, we can determine an optimal transition path and optimal mix of technologies which respects emission limits while minimising costs.

While energy system expansion is not a new problem, the emergence of wind, solar and other intermittent renewable energy sources introduces new challenges. There is a need for flexibility in order to even out local mismatches in time between generation and demand, which can be provided by transmission capacity, sectoral coupling and energy storage units, among others. The less predictable generation and the use of storage in turn make newer energy systems significantly harder to model. This has spurred a renewed interest in the fundamentals of energy systems modelling and motivates the search for more efficient modelling techniques.

In this paper, we are interested in the capacity expansion problem for large-scale energy networks at the transmission level, with a time scale of months to decades. Well-known models addressing this problem include TIMES [1], ReEDS [2], OSeMOSYS [3], PyPSA [4] and Calliope [5]. Theoretically, large energy systems can be modelled quite well with (linear) mathematical programs, allowing the optimisation of both operation and design of the system. However, the systems are large and complex enough that we run into computational limits when building detailed models. Therefore, we must make simplifications and corresponding compromises to accuracy. As an example, PyPSA-Eur [6] is a model of the European energy system consisting of hundreds of nodes over one year at hourly resolution, and takes in the order of one day and tens of gigabytes of memory to run.

Recent advances in computational power are driven by increasing numbers of processing cores, which linear program solvers are not able to take advantage of effectively [7]. Thus, to improve the capabilities of energy system models, we focus on improvements to the models themselves. There are many different ways to reduce the complexity of energy systems models [7], and comprehensive models employ a combination of techniques suited to problem which the model addresses [8]. Basic factors to consider are level of technological detail, spatial resolution and temporal resolution. These factors all influence the size and complexity of the linear program defined by the model. In this work, we are mainly interested in temporal resolution.

Large-scale energy systems are usually modelled at an hourly resolution at best. However, several methods exist to address the number of time steps in energy systems models [9], collectively referred to as time aggregation techniques. A uniform down-sampling of the model (e.g. going from hourly to 4-hour time steps) is perhaps the most basic reduction. A more sophisticated method, called segmentation, is to aggregate adjacent time steps based on how similar the input data for the model is at these time steps. For example, the state of our system might not change much between 02:00 and 05:00 at night, allowing us to aggregate these three hours into one longer step. Finally, the most drastic simplification is to model only a select subset of representative time periods, for example a few typical days per season. However, implemented naïvely, a model using representative time periods can't keep track of the state of charge of storage between periods.

While time aggregation techniques have been the object of much research, up-to-date surveys have still identified significant gaps in the literature. For example, [7] mentions the need for a more abstract or flexible approach to aggregation. Together with the lack of systematic comparison between different studies, we can conclude that there is no consensus yet on the best way of using time aggregation in energy systems modelling.

The use of representative periods specifically is becoming questionable in energy systems which are influenced more and more by the weather. A traditional system with conventional power plants may have a few typical demand profiles for each season, and the behaviour of this system is almost solely determined by the demand input data. However, a system spanning a large geographical region with generation relying heavily on wind and solar power may not have any global typical periods which repeat at all. This is because the operation of such a system depends on many different external variables, and the probability that all these variables (and hence the operation of the whole system) repeat themselves simultaneously in a typical pattern is very low. A similar problem has been identified in [9] in the context of adding representative extreme periods to a model.

In this work, we do away with the traditional use of representative time periods. Instead, we investigate the idea of modelling individual components at different time resolutions, or indeed applying the technique of representative time periods to individual components. Some limited attempts at this have been made previously and are used for inspiration. However, we pursue a synthesised and general perspective on how to use variable and constraint aggregation techniques at the component level to reduce the temporal complexity of energy system models.

Related literature and theories

For comprehensive reviews on the topic of time aggregation in energy system models, we refer to [9–11]. In the following, we merely outline the most relevant work in our context.

As mentioned, modelling (long term) storage presents a particular challenge and is one of the motivating factors for this work. However, while we abandon the model-wide use of representative periods, significant work has also been done recently on reconciling the use of representative periods with seasonal storage. In particular, a number of independent publications [12–15] have pioneered the idea of "linking" representative periods in some way, keeping track of the state of charge of storage between periods. The performance of some of these new methods has been compared on large instance in [16]. However, while linking representative periods takes care of the state of charge of seasonal storage, the more fundamental problem with representative periods (there being no repeating patterns in high-dimensional input data) remain.

Existing literature is sparse on the topic of modelling individual components at different time resolutions. The work in [12, 13] could be seen as modelling seasonal storage at a coarser resolution, but the idea is not investigated as such. To the authors' knowledge, the topic (in the context of energy systems research) has been the most thoroughly investigated in [17]. There, inspiration is taken from literature on the scheduling of chemical plant operations. But although the paper highlights the potential of separate time resolutions, the scope considered in [17] is fairly narrow. The instance on which various component-level time aggregation techniques are tried out is a simple single-node system. While the results are positive but not dramatic, it is acknowledged that the impact on larger systems may be quite different. Moreover, there is much potential for different component-level aggregation strategies.

Research questions

In this work, we address two questions.

1. Is there a reasonably simple energy system model formulation in which the representations of individual components are independently simplified in the time dimension?

This formulation should generalise existing time aggregation approaches such as down-sampling, segmentation and representative time periods.

2. How do we choose appropriate simplifications at the component level, and what is their impact on the performance and accuracy of typical energy system models?

Of course, the proposed simplifications should be compared with existing approaches to evaluate their impact.

Methodology

While we want to simplify energy system models to reduce the computational burden, we should recognise that some components may suffer more from simplification than others. On one hand, for example, the operation of a nuclear plant or seasonal energy storage may not vary much throughout a day and could be modelled at 6-hour intervals. On the other hand, the operation of batteries, which often work with daily cycles, may need to be modelled at an hourly resolution in order to take peaks in demand and production into account. There may also be components, such as gas turbines providing peak generation, whose operation may only need to be modelled in detail during hours or even seasons where peak demand typically occurs. As we outline in more detail below, varying the time resolution at a component level can be achieved by simply aggregating individual operational variables of the model.

It is instructive to compare this approach visually with existing time aggregation techniques. The left drawing in Figure 1 illustrates the operational variables in a model without any time aggregation. Each box represents a variable, and we have arranged the variables by which time step and component they correspond to. The approach of this paper is illustrated on the right in Figure 1, highlighted by the red box. Here, we have aggregated some of the variables, but differently for each component. Contrast this with aggregation by segmentation and representative time periods, illustrated in Figure 2. There, variables have been aggregated uniformly for all the components.

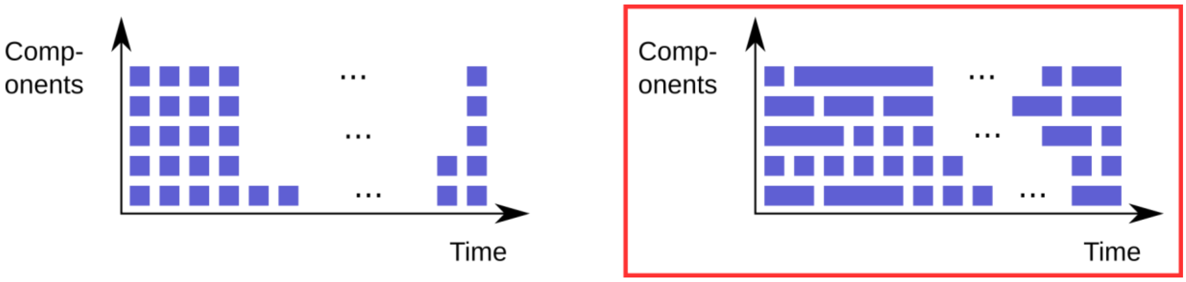

Figure 1: Left: the operational variables in a full-resolution model. Right: the same model, but some of the variables have been aggregated. Each block represents the operational variable (e.g. production level) of a component at a particular time

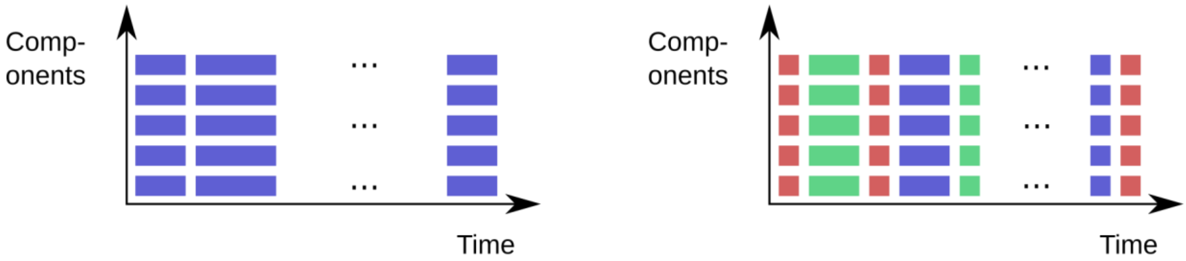

Figure 2: Left: segmentation, where adjacent time steps have been aggregated for all components. Right: representative time periods. In this example, we have three representative time periods indicated by three different colours.

As a theoretical underpinning, we can use the aggregation and disaggregation framework proposed in [18]. Simply put, we can *aggregate* variables $x_1, \dots, x_n$ by replacing all their occurrences in a linear program by a new variable x. This produces a new linear program, potentially with a different optimal objective value. The idea is that if $x_1, \dots, x_n$ are all similar in an optimal solution, then replacing them by x won't change the objective value much.

Dually, we can also aggregate constraints. In the context of energy system models, each operational variable often has one or more simple constraints associated with it. For example, the output of a power plant is at any given time limited by its maximum capacity. Now, if we have constraints $x_i \leq b_i$ for $i = 1, \dots, n$ and we aggregate $x_1, \dots, x_n$ into x, then we can simply replace the constraints by the single bound $x \leq \min_{(i=1,\dots,n)} b_i$.

As we can see, any set of variables and constraints can be aggregated in theory. However, the natural question is which variables (and associated constraints) we can aggregate without changing the objective value too much. There are a few different kinds of aggregations which we could consider. For one, we can aggregate sets of variables, associated with one component, which represent contiguous sections of time. This is analogous to segmentation, but for a single component. Another approach is to use aggregation to create representative time periods for single components. Moreover, while we choose to focus on temporal resolution, variable aggregation may also be applied flexibly to components. For example, sets of components may be aggregated for specific time periods only.

All in all, the approach outlined in this section answers our first research question in the affirmative.

Expected results

The second research question, asking how effective the flexible aggregation technique can be, is harder to answer. We plan to try out a variety of different aggregation techniques and levels of aggregation on large instances of energy systems in order to compare their performance and accuracy to that of a full resolution model. We will use the PyPSA-Eur as a reference and a basis for experimentation. In this way, we hope to elucidate which kinds of components deal well with which kinds of simplifications. The performance and accuracy of our tests will additionally be compared to existing time aggregation methods, and indeed incomplete solves of a full resolution model.

Since our aggregation method is a strict generalisation of previous time aggregation approaches, our results in terms of performance and accuracy are expected to be at least as good as for previous approaches. What remains to be investigated is whether the flexible time aggregation approach leads to significant enough improvements to justify its use.

Finally, following [18], it is also possible to calculate bounds on the objective function of aggregated models without solving the full resolution model. These bounds will be investigated and compared with empirical results in order to evaluate their usefulness. This may provide an effective tool for designing new simplifications, and lend new insight into the accuracy of existing time aggregation techniques as well.

Conclusion

In this work, we introduce a new, flexible way of simplifying energy system models by directly aggregating operational variables for individual components. In this way, we hope to enable good approximations of large-scale energy systems with a big share of wind, solar and seasonal storage technologies. Moreover, our formulation unifies many previous time aggregation techniques.

For future research, the most important remaining open question will be how to choose the variables to aggregate. Looking to the literature on how to choose representative time periods, this may well involve clustering of the input data.

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