A METHOD FOR MODELLING OF HYDRO STORAGE POWER PLANTS IN POWER PLANT DISPATCH MODELS WITH ROLLING HORIZON APPROACH

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1 Overview

The demands of system integration of renewable energies rises the challenges for energy system modellers by increasing the necessary temporal resolution. To reduce the execution time of energy system optimization problems, the problem is sometimes decomposed into sub-problems with shorter time intervals [1]. The sub-problems are then solved successively and individually. In this way, parameters from future time intervals are not considered in previous sub-problems and computing becomes more efficient. This makes it possible to solve the whole problem in a reasonable execution time.

There are different approaches for time decomposition [1]. In the rolling horizon approach, the decomposed sub-problems overlap in time, and variables are passed on as fixed values to the next sub-problem. In this way, the next sub-problem has the necessary information due to the fixed values at the beginning of its time horizon.

The rolling horizon approach is widely used in power plant dispatch models and is either motivated by including uncertainty or the reduction of computation time [2, 3]. In dispatch models, the power plants are scheduled based on their variable costs. Therefore, no information on the long-term future is necessary. The short time horizon of the sub-problems is sufficient for the decision on power plant dispatch. In order to make a profit, the power plants must be able to cover both their variable and fixed costs. For thermal power plants, the variable costs are mainly determined by the costs for fuels and, increasingly, emission certificates.

In contrast, there are hardly any variable costs associated with a hydro storage power plant. Instead, opportunity costs are calculated and a value is attached to the water in the reservoir [4, 5]. Storage power plant operators weigh the use of water in the present against the use of water at a future point in time. The dispatch decision of seasonal storage must take into account long time horizons, since the use in the present can prevent or restrict the use in the future. The dispatch decision depends much more on the current storage level, the expected future inflow of water and the future price development on the electricity market. Since the storage volume of a reservoir is limited, the water should be used as economically as possible to serve the price peaks on the electricity market. If, for example, a decision is made not to use the storage power plant to its full extent and very high inflow volumes should occur in the future, an excess of water in the reservoir is possible. In the worst case, this implies that water has to be dumped and results in lower revenues compared to the date of the previous decision.

This is why the short time horizon of the sub-problems in rolling horizon approach is not sufficient for hydro storage power plants, as seasonal storage is overly dispatched in the first sub-problems and leads to shortages later on.

The problem has been recognized and approached in different ways. [6] first solve a perfect foresight model that covers the entire time horizon and aggregates the production units to reduce the computational burden. Their heuristic also focuses on other decomposition methods. Then, the overall accuracy is evaluated taking into account two countries without focus on hydroelectric power plants. [7] applies the rolling horizon approach and combines it with stochastic modelling. [8] applies a nonlinear control model and tests different time horizons of the rolling horizon.

In this study, we aim at reducing the calculation time of a European-scale energy system model (ESM), and at mimicking a perfect-foresight solution of its linear dispatch problem. In fact, the full perfect-foresight problem is intractable with conventional computers. We focus on the integration of hydro storage plants into a rolling horizon approach and develop a 3-step procedure for the modelling of storage power plants in energy system models. The three steps gradually reduce the aggregation of time slices and, step- by-step, introduce more information to the model. The expected benefit is a detailed consideration of the hourly demand and renewable energy characteristics in the dispatch of hydro storage plants. The result is a heuristic to solve the perfect-foresight problem.

The remainder of this paper is structured as follows. Section 2 describes our proposal for modelling storage power plants in ESMs using rolling horizon planning as a time decomposition technique. Section 3 presents the results and finally section 4 provides brief conclusions.

2 Methods

In 2.1, we summarize different time decomposition techniques. Afterwards, 2.2 describes the modelling of storage power plants in perfect foresight ESMs. Finally, 2.3 presents the additional steps required for the modelling of the hydro storage power plants in rolling horizon ESMs.

2.1. Time decomposition techniques

Perfect-foresight models are characterized by the neglect of uncertainty on the future development of variables that in reality follow stochastic paths. Actors are assumed to have perfect information on future events such as electricity demand in a given hour or the feed-in from renewable energies. Energy system analysis typically uses perfect-foresight solutions as best- case scenarios, or, in the case of cost minimization, as lower bounds of what could be achieved in theory. However, the problems of energy system analysis, where typically multiple regions, thousands of processes and long time periods are considered, can be too complex to be solved in a reasonable time.

In order to reduce the complexity of the perfect-foresight optimization problem, time decomposition techniques divide the planning horizon into smaller time periods. In this way, the parameters from future time periods are not considered in the optimization and the required computing power and computing time is reduced.

Mainly, two paradigms are applied for reducing the temporal dimension of the problem. Rolling horizon and myopic approaches mainly differ in whether the time horizons of sub-problems overlap, or not.

Myopic: The myopic approach assumes that there is no overlap of the short time periods. The optimization problem of each time period is solved individually and the results are fixed. Variables that cover more than one time period are passed as fixed start values to the optimization problem of the next time period. This approach can, however, lead to a discontinuous development path, as for each sub-problem, only a solution is calculated that is optimal for the respective planning horizon, but not for the following time period. On the other hand side, it was argued that myopic optimization resembles the actual circumstances of real decisions more closely [9]. This approach thus seems to be more appropriate for long- term investment planning models, as technical constraints of power plants in dispatch model require a continuous operation.

Rolling Horizon: In contrast to the myopic approach, the time horizons of the sub-problems overlap. For the following sub-problem, a subset of variables corresponding to the last time slices of the previous sub-problem, is handed over as fixed values. In this way, the following sub-problem starts with fixed initial values, but can determine a solution for the remaining du- ration of the overlap of the time horizon, since it has a broader foresight. The continuity of the results is thus secured, and technical constraints are not infringed by abrupt changes, a fact that makes rolling horizon techniques favourable for reducing the temporal dimension of dispatch models.

To sum up the previous discussion: In power plant dispatch models, the information about previous optimizations is important for the behaviour of the power plants. The dispatch of power plants can depend on technical constraints that encroach on two or more sub-problems. For this reason, the rolling planning approach is mainly used in many power plant dispatching models and also in our model.

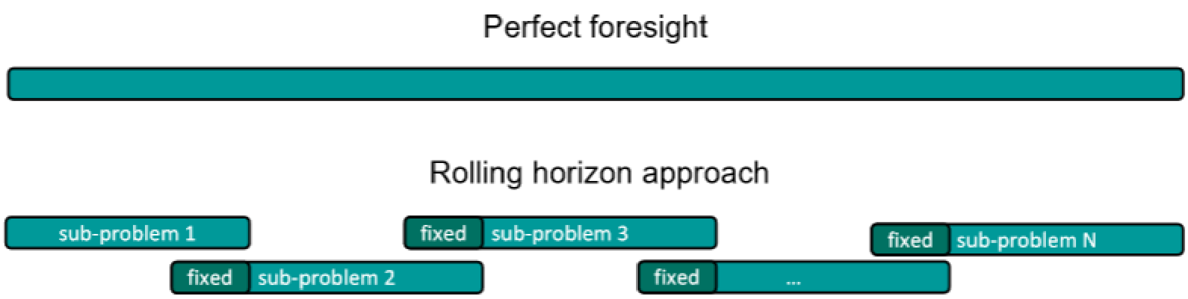

Figure (1) Model decomposition techniques based on model time resolution

2.2. Perfect Foresight modelling

The associated storage reservoir plays an important role in the modelling of storage power plants. The water that is used for electricity production can only be drawn from the existing storage reservoir at a storage power plant, thereby reducing the storage level. At the same time, however, there are natural tributaries from rivers, brooks or directly by precipitation, which lead to an increase in the storage level.

The storage level has a lower and an upper limit. If the storage level is already at the upper limit and there is a water inflow greater than the maximum amount of water that can be used for electricity production, the excess amount of water must be discharged unused. Due to the importance of the reservoir, all these water flows have to be considered in the model. The data itself are the input profiles of the energy system. Examples of these input profiles are the electricity demand, the weather-dependent electricity production from RES and the natural inflows to the reservoirs of hydro storage power plants.

Equation 1 determines the development of reservoir levels RLu,t for each unit u in time t. The level RLu,t at time t is calculated by adding the storage level at time t−1, the natural water inflow into the storage InFt, the unused amount of water OFu,t and the amount of energy PLpc,y,t used in storage power plants for electricity production at time t.

$$RL_{u,t} = RL_{u,t-1} + InF_t - OF_{u,t} - PL_{pc,y,t} \tag{1}$$

$$\forall pc \in PC_u,\ \forall u \in U^{storage},\ \forall t \in T$$

We determine upper and lower levels of the reservoir, as well as starting and end values exogenously.

If no end values for a year were set, the storage would be discharged by the end of the operation period. This is because, in the case of cost minimisation, the storage power plants would be dispatched for electricity production due to their low variable costs until their reservoirs are depleted. However, a storage level at the minimum at the end of the year would not be a realistic scenario for most regions of Europe, since some of the water is needed in the beginning of the following period.

Restrictions hold for the upper and lower level of the reservoir. We selected the maximum and minimum historical values of the aggregated storage reservoirs of each unit as the values of the upper and lower limits of the respective storage levels.

2.3. Additional modelling for rolling horizon models

The use of hydro storage power plants depends in part on events that can- not be foreseen within a short-term optimisation period, such as a week. However, in order to enable year-round optimisation of the use of the stor- age power plants in hourly resolution, the optimisation process is divided into three optimization steps. For a more precise calculation of the storage power plants, we optimize the model repeatedly with lower time resolution and use the results of the previous optimization as input for the next step (See Figure 2).

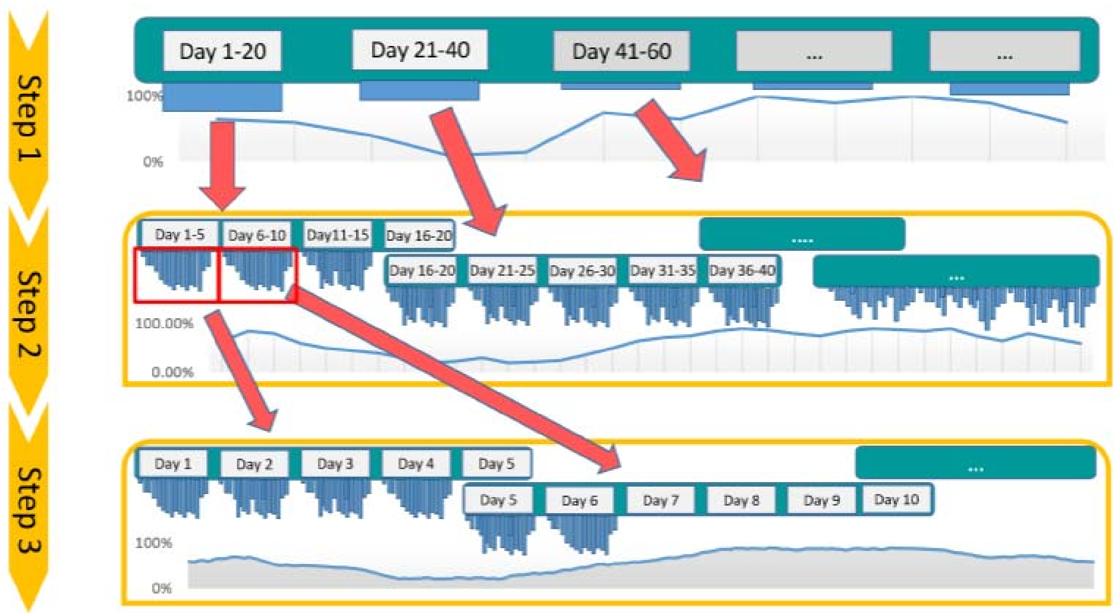

Figure (2) Optimization steps

In step 1, a perfect foresight model s executed over 365 model time slices (each day aggregated to one time unit). In step 2, the results of step 1 are used to constrain reservoir usage, and rolling horizon planning is performed over 20 days, while daily patterns are introduced to the model. Finally, in step 3, a rolling horizon planning over 5 days each is optimized constrained by the water demand calculated in step 2.

We think of all data as matrices (Xd,h), where rows d represent days, while columns h ≤ 24 represent the hour of the day. The different aggregation steps can now be described relatively simple: in the first step, we add up data along each row. In the second step, we add up data column-wise.

2.3.1 Optimization step 1

In optimization step 1, a simplified time structure is used. Both the input data of the water inflows as well as the electricity demand and the generation from renewable energies are added up over a whole day to a single time unit. We optimize a simplified perfect-foresight model over 365 time slices, instead of over 8760 hours. Each of these aggregated time slices represents the 24 hours of a day in a single value. Equation 2 demonstrates the simple aggregation. In step 1, n is equal to 24.

$$X_d^{model} = \sum_{h=1}^{n=24} X_{d,h} \tag{2}$$

By reducing the time structure it is now possible to solve the optimization problem of the first step with perfect foresight over all 365 time slices. However, the only result relevant of this optimization step is the operation of the hydro storage power plants.

The results of step 1 are used to constrain the amount of water to be used in each period of step 2. Some constraints, such as load change behaviour of power plants between the different hours or pumped storage power plants, are ignored in the first step. The second step also has a simplified time structure, but already includes the daily patterns of demand and renewable production.

2.3.2 Optimization step 2

In contrast to the previous step, we no longer aggregate the data of consecutive hours, but data of the same hours of consecutive days. We sum up now by column, instead of adding up rows as before. In order to be able to integrate the load changing behaviour and pumped storage power plants into the operational planning, the daily structure must be preserved.

While in the first step, each time slice in the model represented 24 real hours, in the second step, each time slice represents five hours. Each successive five days are aggregated to a model day, but a model day has 24 hours.

For example, the data of the first hour of the first day with the data of the first hour of the second, third, fourth and fifth day. In this way, the typical intra-day load fluctuations are maintained. This allows for a more realistic dispatch of the plants. As this increase in time slices from 365 to 1752 already renders the model increasingly complex, as variables increase exponentially with time, we already shift to a rolling horizon approach to minimize calculation time. The model in this step includes 73 model days, assigned to 19 optimization problems.

$$X_{d,h}^{model} = \sum_{d=1}^{n} X_{d,h} \tag{3}$$

In the example with $n = 5$ thus five consecutive days together form a model day. Any other level n of aggregation can be chosen as well, however, factors of 365 are most convenient, as those produce no remainder that has to be integrated as well.

Since this time structure is already much less aggregated than in the first step, no year-round optimization of a single optimization problem can be performed with perfect foresight. Instead, the problem is divided into sub-problems, and an overall solution for an entire year is obtained by a rolling horizon planning of the sub-problems. We assign the created 73 days to 19 optimization problems. The first phase of step 2 comprises five real days, one model day, while all other phases comprise 20 real days, 4 model days (1 model day x 1 + 4 model days x 18 =73 model days). Any other division into sub-problems is thinkable. However, as 73 is a prime number, any division will end up in an uneven distribution of model days to sub- problems and thus entails a human decision to be made.

A crucial decision in designing rolling horizon models is to define an appropriate overlap. We decide to let sub-problems overlap one model day (see Figure 2). Thus, each sub-problem, with the exception of the first, comprises of a five-day phase defined above and the last model day of the previous phase. The overlap of the partial problems serves to transfer operating states of power plants to the next sub-problem. As operation constraints of power plants do not extend to periods longer than one day, we do consider the overlap as appropriate and refrain from further evaluation.

As explained above, hydro storage levels from step 1 serve now to con- strain the operation of the storage plants in every sub-problem. The storage levels of step 1 of the days that comprise a sub-problem in step 2 are added up and define the maximum commitment.

From the second optimization step, the results of the resource planning of the storage power plants are used in the final step. The storage operation results of each model day comprising five real days are summed up and then constrain the maximum amount of water to be used for each phase of the third optimization step. Model days in step 2 have been chosen to represent one sub-problem in the third phase.

2.3.3 Optimization step 3

In this last step, the operation of the full electricity system over the full period of time are calculated. Historical data of water inflows, electricity demand and feed-in from renewable energies serve are input to the model. This last optimization step contains all constraints such as minimum operating times and down-times of power plants more detailed. Each partial problem comprises exactly one phase as well as the last 24 hours of the previous phase.

We so far have assumed that power plant operation is based purely on economic considerations and that storage operation was only constrained by the volume of the reservoir, and starting and end values.

2.3.4 Minimum water flows

There are requirements that guarantee a minimum water flow rate, which is laid down by law in European countries (e.g., in Germany: Paragraph 33 of the Water Resources Act - Wasserhaushaltsgesetz [10]). Staunching of an above-ground watercourse or the release of water from an above-ground watercourse is only permitted, if thresholds required for environmental reasons are complied with.

In order to achieve more realistic results, another constraint must be imposed to the model: a minimum water flow. For this, the level of the minimum water flow must first be determined. We chose a similar approach as the study by Hecker et al. [11]. They make a the assumption that the historical daily minimum of the water flow represents the minimum water flow.

In our analyses, we use the historical load of the hydro storage power plants $P_{u,t}$ for unit u in time t to define the minimum loads. In contrast to that study [11], however, we aggregate the data, so that no hourly load profiles are used in the first step. Therefore, a different approach is chosen for the first step. Let $Q(p)(X)$ denote the p-th quantile for $0 < p \leq 1$ of a set $X \subset R$. First, the minimum flows are aggregated over seven consecutive days (168 consecutive hours) and the 0.05 quantile of these flows is used to determine the daily minimum flow quantity instead of using the daily minimum natural flow amount (see Equation 4). Daily minimum flows would lead to incorrect results due to the outliers in data.

$$MinP_u = Q(0.05)\left\{ \sum_{k=i}^{i+168} P_{u,k} \middle| i \in \{1, \ldots, 8593\} \right\} / 7 \tag{4}$$

$$\forall u \in U^{storage}, \forall t \in T$$

In the second and third steps, Equation 5 is used to identify the mini- mum flows. This time, the 0.01 quantile of the hourly values over a period of 30 days are used. In this way, higher minimum loads due to weather conditions are taken into account and the flexibility of resource planning is not unduly restricted. The usage of the minimum values could lead to the use of outliers or errors in the data as minimum flow levels.

First we calculate the 0.01 quantile of the hourly values for each period of 30 days in the year. We then use the resulting minimum flows in each 30-day period of the model period.

$$MinP_{u,i} = Q(0.01)\Big\{P_{u,h} \big| h \in \{720*i+1,,720*i+2,\cdots,720*i+720\},\; i \in \{0,1,..11\}, h < 8760\Big\} \tag{5}$$

$$MinP_{u,t} = MinP_{u,i}, \text{when } (720*i < t \leq 720*i+720) \tag{6}$$

Equation 7 ensures that in the selected time period, the duration L at least the specified mininum water flow quantity is discharged from the hydro storage power plant. It does not matter whether this amount of water is used for power production or not. To this end, the difference of the storage levels between the time ($t - l$) and the time (t) is measured and the sum of all inflows of this period is calculated. L is the duration of the period during which the calculated minimum flow is applied in each step. In our example application, we have always calculated the daily minima and applied them to the model days. In step 1 it is therefore 1, since we have aggregated each 24 hours to one hour. In steps 2 and 3, L is 24, because in these steps, we maintain the hourly resolution of days.

$$RL_{u,t-L} - RL_{u,t} + \sum_{i=t-L}^{t} Inf_{u,i} \geq MinP_{u,t} \tag{7}$$

$\forall u \in U^{storage}$, $\forall t \in T$

3 Evaluation

For evaluating the proposed method, we generate a test case. We build upon historical data from the year 2015. The model we use can be described as an energy system for Europe, where countries are nodes in an electricity network. The power plant fleet is considered in high detail, while renew- able production and demand are exogenous. The Description of PERSEUS model can be found in [3, 12]. We compare the storage levels that result from the above modelling procedure against historical storage levels that are calculated based on the data available from ENTSO-E. Inflow of the reservoirs in the model are calculated based on the storage levels and power production reported by ENTSO-E. As main measurement of accuracy of the results with respect to historic data, we assess the correlation coefficient between history and model data. As this correlation is mostly an indicator for the accordance of the general trend for non-stationary time series (spurious correlation), we additionally assess correlation coefficients of the hourly change of the storage level. This can be interpreted as an indicator of how precise also hourly patterns are matched. Figure 3 shows a comparison of the storage levels between the historical values and the model results.

The storage volume curve of the modelled Norwegian storage power plants shows a correlation coefficient of 0.9962 with the historical curve of 2015. And even the hourly differences still reach a degree of correlation of 0.9179. The results for Sweden differ only slightly from the Norwegian results.

The modelling of the Swedish storage power plants achieves a correlation degree of 0.9977 compared to the historical course of 2015, or a correlation degree of 0.9065 related to the hourly differences of the two time series.

In the case of Austria, the difference compared to the large storage volumes in Sweden and Norway is evident. In contrast to Norway and Sweden, Austria lies in the middle of Europe and is therefore also used as an electricity transit country. With the neighbouring Germany, there is also a high level of interconnection capacity. The Austrian storage power plants are used to balance intermittent electricity generation of renewable energies. Furthermore, Austria's storage volume is relatively small, so that there are strong fluctuations in the storage process when the flexibility potential is exploited. The correlation is 0.9401. However, the correlation of hourly differences is much lower with 0.4695.

Romania is located at the external borders of Europe, a country that also has a low storage volume, and a significantly lower minimum water supply than Austria. In addition, the residual load curve is more uniform, which also means that the remaining power plant fleet runs continuously and there are only minor fluctuations in the storage level due to individual thermal power plants being switched on or off. The degree of correlation between the historical storage volume curve and the modelled Romanian curve is 0.9657. The hourly differences between two storage levels show a correlation of 0.5075, indicating that precisely recreating hourly storage levels is a difficult task. However, the main objective of this work is the integration of the seasonal course of the seasonal storages, which is done already in a high satisfactory level. Recreating hourly dispatch is not possible also for any power plant technologies anyway, as the markets and so dispatch of the power plants is not optimal in reality. This also applies to the other power plant technologies, so that an optimal but not realistic dispatching of the other power plants in turn influences the dispatching of the storage power plants. Some countries also make modelling even more difficult. In Portugal, the minimum water supply is indirectly switched off during steps 2 and 3, as historical data show that no water is used for electricity generation for a few hours. The correlation between the historical and the modelled storage history curve is 0.9196 for Spain and 0.9258 for Portugal, and 0.6749 for Spain and 0.3424 for Portugal when hourly differences are considered.

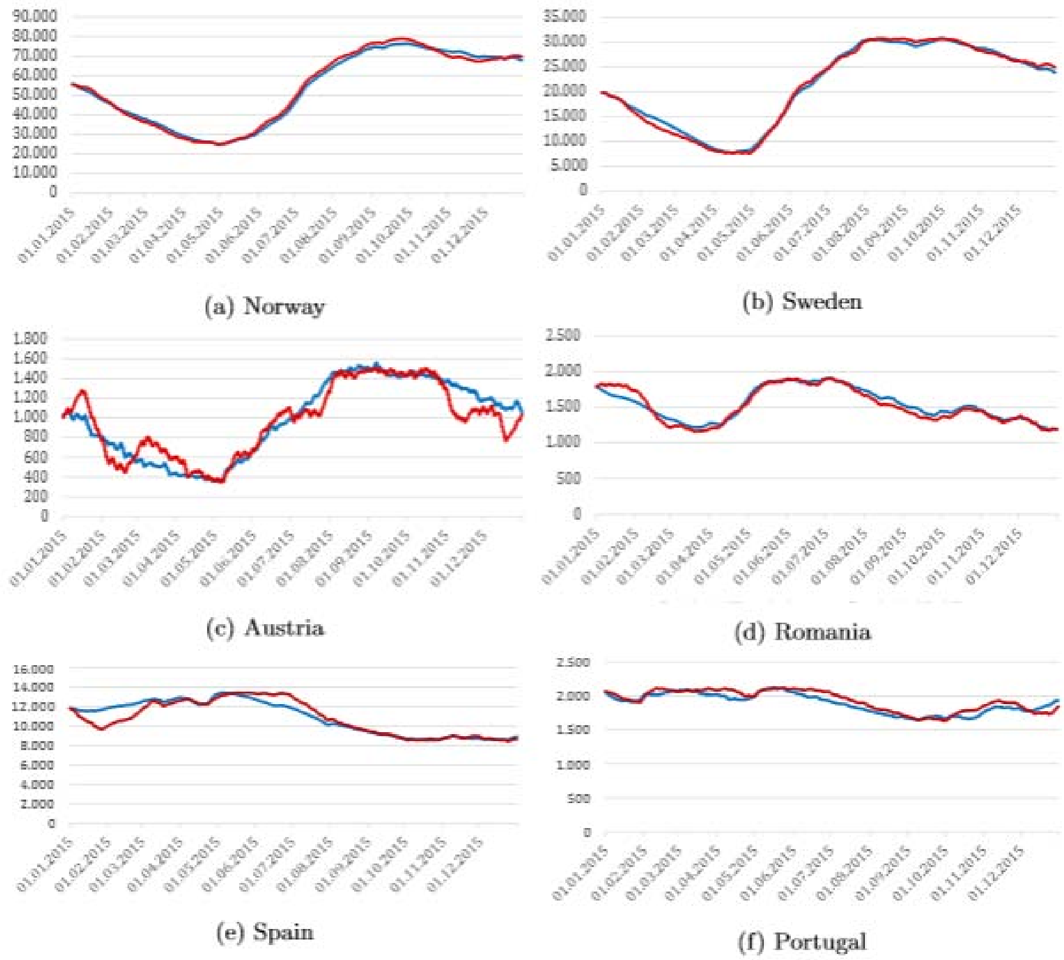

Figure (3) Comparison of the storage levels of the model results and the historical values - in GWh - Blue: Historical Values, Red: Model Results

4 Conclusions

The application of the presented method allows the modelling of storage power plants in power plant dispatch models with rolling horizon. A big advantage of the method is that only new model restrictions have to be added, and time resolution of the model have to be adapted. No major changes to the basic energy system model have to be made. The method can therefore be transferred relatively easily to other energy system models. However, an analysis with further data from other years is necessary, also to determine values for the minimum flow levels.

Future work also should assess whether the introduction of the second step does have benefits for the precision of modelled storage operation. We expect that the correlation of the changes in hourly storage volume is considerably improved by the introduction of the second step, as the second step introduces information on the daily profiles to the final model.

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References

[1] J. Haas, F. Cebulla, K. Cao, W. Nowak, R. Palma-Behnke, C. Rah- mann, and P. Mancarella. Challenges and trends of energy storage expansion planning for flexibility provision in low-carbon power sys- tems – a review. Renewable and Sustainable Energy Reviews, 80:603 – 619, 2017.

[2] Hans-Martin Henning and Andreas Palzer. A comprehensive model for the german electricity and heat sector in a future energy system with a dominant contribution from renewable energy technologies—part i: Methodology. Renewable and Sustainable Energy Reviews, 30:1003 – 1018, 2014.

[3] Tobias Heffels. Kraftwerks- und Speicherbedarf bei hohen Anteilen erneuerbarer Energien. PhD thesis, 2015.

[4] Stein-Erik Fleten and Trine Krogh Kristoffersen. Short-term hy- dropower production planning by stochastic programming. Computers Operations Research, 35(8):2656 – 2671, 2008. Queues in Practice.

[5] Stein-Erik Fleten and Trine Krogh Kristoffersen. Stochastic program- ming for optimizing bidding strategies of a nordic hydropower producer. European Journal of Operational Research, 181(2):916 – 928, 2007.

[6] Timo Breithaupt, Thomas Leveringhaus, and Lutz Hofmann. Heuristic solution of a joint electric control reserve and wholesale market model. International Journal of Modeling, Simulation, and Scientific Comput- ing, 10(02):1940001, 2019.

[7] Vincent Guigues and Claudia Sagastiza´bal. The value of rolling-horizon policies for risk-averse hydro-thermal planning. European Journal of Operational Research, 217(1):129 – 140, 2012.

[8] Gerrit Erichsen, Tobias Zimmermann, and Alfons Kather. Effect of different interval lengths in a rolling horizon milp unit commitment with non-linear control model for a small energy system. Energies, 12:1003, 03 2019.

[9] Sonja Babrowski, Tobias Heffels, Patrick Jochem, and Wolf Fichtner. Reducing computing time of energy system models by a myopic ap- proach. Energy Systems, 5(1):65–83, 2014.

[10] Mindestwasserführung. Kapitel 2 - Bewirtschaftung von Gewässern (§§ 6 - 49), Abschnitt 2 - Bewirtschaftung oberirdischer Gewässer (§§ 25 - 42).

[11] Constanze Hecker, Evamaria Zauner, Christoph Pellinger, Luis Carr, and Stephan H¨otzl. Modellierung der flexiblen energiebereitstellung von wasserkraftwerken in europa. Proceedings of the 9th Internationale Energiewirtschaftstagung (IEWT), Vienna, Austria, pages 11–13, 2015.

[12] Heidi Ursula Heinrichs. Analyse der langfristigen Auswirkungen von Elektromobilit¨at auf das deutsche Energiesystem im europa¨ischen En- ergieverbund. KIT Scientific Publishing, Karlsruhe, Germany, 2014