The Importance of High Temporal Resolution in Modeling Renewable Energy Penetration Scenarios

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Abstract

Traditionally, modeling investment and dispatch problems in electricity economics has been limited by computation power. Due to this limitation, simplifications are applied. One common practice, for example, is to reduce the temporal resolution of the dispatch by clustering similar load levels. The increase of intermittent electricity from renewable energy sources (RES-E) changes the validity of this assumption. RES-E already cover a certain amount of the total demand. This leaves an increasingly volatile residual demand to be matched by the conventional power market.

This paper quantifies differences in investment decisions by applying three different time-resolution residual load patterns in an investment and dispatch power system model. The model optimizes investment decisions in five year steps between today and 2030 with residual load levels for 8760, 288 and 16 time slices per year. The market under consideration is the four zone ERCOT market in Texas.

The results show that investment decisions significantly differ across the three scenarios. In particular, investments into base-load technologies are substantially reduced in the high resolution scenario (8760 residual load levels) relative to the scenarios with lower temporal resolution. Additionally, the amount of RES-E curtailment and the market value of RES-E exhibit noteworthy differences.

Keywords: Wind power integration, temporal-resolution, electricity market, benders decomposition

JEL-code: C61, O21, Q21, Q41

1 Introduction and Motivation

Adding a high share of variable wind power to an existing power system changes the optimal operation of the remaining power plants and therefore also the investment calculus for new generation capacity. With low, near-zero variable costs, wind power plants are usually the first generating units that are dispatched in the power system. It is therefore common to subtract wind generation from total demand to form the time-varying residual demand that the remaining generation units must be dispatched to meet. Because of these dynamics, wholesale power prices tend to be lower in hours with high wind power generation because the lower residual demand can be met by cheaper marginal units (Sensfuß et al., 2008; Munksgaard and Morthorst, 2008; Traber and Kemfert, 2010 ; Green and Vasilakos, 2010). The altered dispatch patterns and wholesale power prices, however, also impact the investment calculus of new power plants as demand rises or existing units retire, and those new investment impacts further influence dispatch and pricing results (e.g. Dena, 2005).

Deriving an economic value of wind power to a power system based solely on the static perspective of a dispatch model or empirical data is therefore not sufficient. The dynamic adaptation processes in which new power plant investment decisions are also considered is critical in accurately simulating the impact of wind on the power system. A valid way to accurately capture the value of wind power is therefore to compare a power system without wind power and consequently without the adaptation effects due to wind power with a system that adapts to the wind power penetration through appropriate investment decisions.

Despite the interrelationship between short-term dispatch results and longer-term investment decisions, modeling the combined impact of both effects has proven challenging. Two general research streams exist in the literature: the first uses high-temporal resolution dispatch models to capture the short-term price effects due to the variability of wind power, whereas the second uses capacity-expansion investment models to illustrate the longer-term adaptation processes of the remaining power system. To try to capture longer-term investment effects, dispatch models sometimes use power plant portfolios that are generated from an investment model (see e.g. Green and Vasilakos, 2010), but in other cases impacts on investment decisions are ignored (e.g. Sensfuß et al., 2008).

Some studies have sought to explicitly combine dispatch and investment optimization decisions into a single modeling framework in order to more-accurately capture the benefits and impacts of wind power on the power system (Neuhoff et al., 2008; NREL, 2008; Dena, 2005). Due to the high computational demands of accurately modeling the combined dispatch and investment optimization problem, however, a reduction in model complexity is usually required. One typical way to do this is to reduce the temporal resolution of the modeling framework; for example, rather than dispatching the system on an hourly basis over entire years, instead selecting a smaller number of broader time slices to evaluate.

Reducing temporal resolution in this manner may be appropriate in systems without high penetrations of variable generation because, for example, every workday evening within a season may have a relatively typical demand pattern that does not deviate inordinately from one day to the next. Adding significant quantities of variable generation, however, can change the residual load substantially on an hourly basis. In order to capture these effects, either a model with a higher temporal resolution is required or the addition of correction factors may be needed to try to approximate the correct result. To date, however, little research has been published on the impact of model-based temporal resolution on modeling results in instances with high levels of wind penetration.

To explore the impact of temporal resolution on dispatch and capacity expansion results, a model that can account for both hourly dispatch and long-term capacity expansion has been constructed. In this article, the results of the model under three different time resolutions are computed. The high-resolution case has 8760 h per year, allowing for hourly dispatch decisions to be considered when determining optimal capacity expansion and other results. The medium-resolution case evaluates 288 h during the year, reflecting typical days by season as has been used in dena (2005). The low resolution case has just 16 broad time slices,[1] which follows the approach used by NREL's ReEDS model as used to evaluate a high penetration wind scenario for the U.S. (NREL, 2008), but without the

[1] The 288 h resolution case assumes typical patterns for workdays, Saturdays and Sundays within each season and therefore averages e.g. the third Wednesday per month each season to create a "typical" workday. The 16 time slice approach averages similar load situations per season in a broader approach, e.g. all night hours within one season.

correction terms utilized by ReEDS.[2] In all instances, the model results presented here loosely simulate the power system in Texas, home to the largest wind power market in the United States.

The aim of this article is to broadly evaluate the influence of model-based temporal resolution on the impacts of high penetrations of wind energy on the power system, and not to specifically evaluate any individual pre-existing models. By learning more about how temporal resolution impacts results, it is hoped that models might be improved, either by increasing temporal resolution or – where modeling complexity does not allow increased resolution – by adding correction factors to try to approximate the true impacts of wind energy on power systems. A better understanding of the impacts of wind on the power market might also assist climate modelers to take these factors into account when evaluating alternative approaches to reducing global carbon emissions using models that, because of their geographic and sectoral scope, are unable apply high time resolutions (e.g. IPCC, 2007). Even where model changes are not possible, the results that follow may at least provide an indication of how "inaccurate" low-temporal-resolution models might be in simulating the impacts of high penetrations of wind energy.

In order to capture the temporal resolution effects, two specific scenarios (with the three temporal resolution cases of 8760 h, 288 h, and 16 time slice) are presented in the pages that follow. The first scenario contains no additional wind power deployment after 2008, and the model is run under all three temporal resolutions. The second scenario adds a substantial quantity of additional wind generation to demonstrate how that expanded penetration of wind energy impacts investment decisions and dispatch results relative to the first scenario, again under all three temporal resolutions. By this approach, first the temporal resolution effects can be analyzed and second, the particular wind energy integration challenges can be analyzed under different temporal resolutions.

The remainder of this article is structured as follows. The second section describes the structure of the model used in the present study: "**T**he **H**igh temporal resolution **E**lectricity-market **A**nalysis-model"

[2] ReEDS seeks to capture these effects by using one additional "superpeak" time slice to account for the peak reserve requirement and a "curtailment factor" to more-accurately estimate curtailment. The accuracy of these corrections is not addressed in the present study.

(THEA). The third section lists the key assumptions and summarizes important results from the model, while also discussing the observed effects of temporal resolution on model results. Finally the fourth section concludes with an overview on the factors that need to be taken into account when high wind penetration cases are modeled.

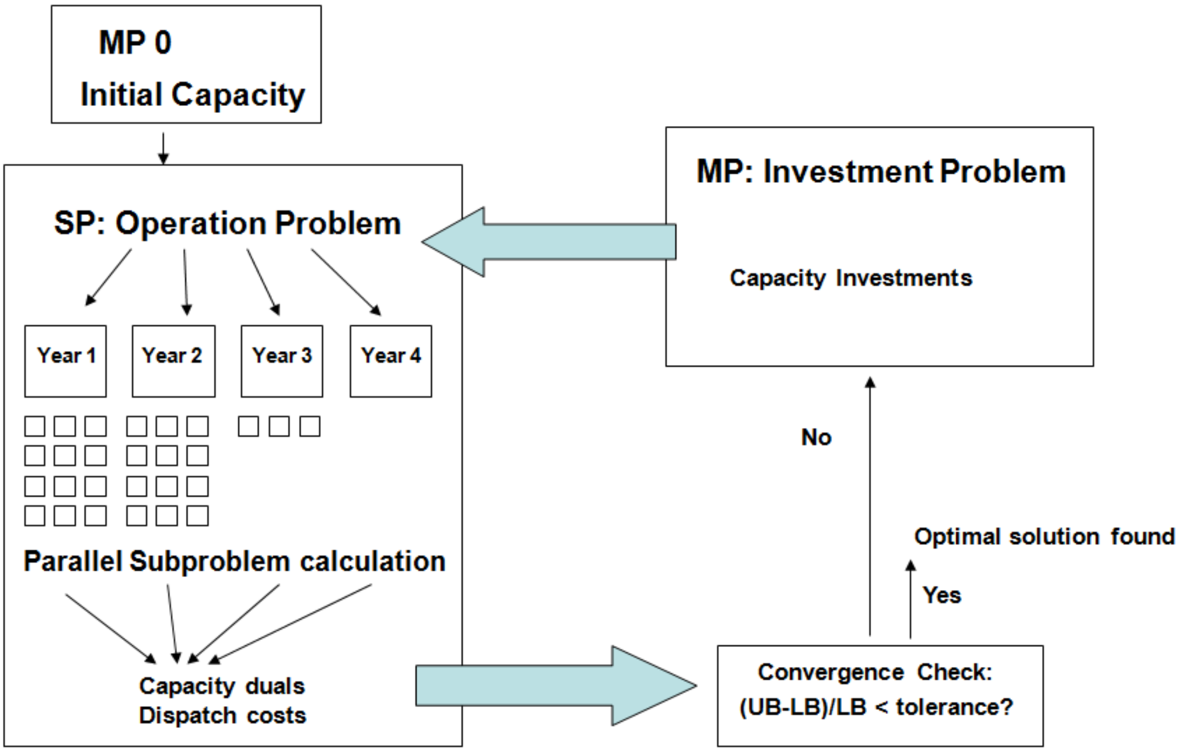
2 Methodology

THEA is a linear optimization dispatch and investment model. The hourly dispatch is enabled by the implementation of a decomposition technique. Investment decisions are computed in 5-year steps until 2070. Because of the end-time issues of investments with a long lifetime, results are only considered until 2030. The capacity mix is determined by investment decisions, which themselves are impacted by the dispatch part of the model, which provides information on efficient capacity adaptations in form of duals of the capacity restriction in an iterative algorithm that will be explained below. The hourly dispatch considers fuel-type fleet investments in order to keep the problem linear (i.e., the model considers all CCGTs within one vintage class as a single unit, and therefore does not evaluate distinct individual plants). The age structure of the existing fleet is mirrored by vintage classes, which take technology developments into account (e.g. efficiency). The coal fleet has six different vintage classes, the CCGT fleet four, the OCGT fleet three and the nuclear fleet two. Existing hydro power capacities are also included, but new investments are not possible due to the natural resource restrictions. THEA optimizes the energy exchange between different price zones, which are restricted by exogenous net transfer capacity (NTC) parameters. The dynamic temporal approach of consecutive hours considers start-up costs and part-load inefficiencies. In order to account for some electricity market restrictions, positive and negative reserve market requirements are implemented. Flexibility is added to the power balance between demand and supply by an option to curtail wind power in case of oversupply.

To allow efficient solutions to the dispatch and capacity expansion problem in such a high temporal resolution, an approach that was first presented by Bender (1962), and is known as “Benders

Decomposition”, is implemented. Based on the duality theory, large mathematical problems can be decomposed into smaller problems by fixing the complicating variable and optimizing it through an iterative algorithm that converges when an optimal solution is reached. Côte and Laughton (1979) presented an initial application of Benders decomposition to power system optimization and proved its advantages for a simple investment and operation problem in terms of memory requirements and solution times. The approach has been further applied for stochastic and integer programming applications, while the challenge of utilizing the approach for “real world” power systems has been summarized by Wang et al. (1996): “Methods of Benders’ decomposition are somewhat complicated, and their application may be computationally impossible for large power systems”. Fortunately, the latter concerns have subsequently been addressed by the recent trend towards high-performance-computing (HPC), thereby overcoming computational challenges. To the knowledge of the authors, THEA is the first application of Benders’ Decomposition that utilizes a dynamic approach by computing investment decisions in five-year steps rather than as one single investment decision for the year under observation, while also making those decisions on the basis of full dispatch years with a maximum of 8760 hours each. In order to enable the computation of this complex problem, THEA adds one additional tool from recent HPC developments: dispatch is calculated in a monthly decomposed parallel mode. The advantage of this latter approach is that while a global model utilizes only one processor core, THEA uses all available cores of the modeling server. In other words, depending on the amount of the available cores of the modeling server, up to 132 months of the eleven considered investment years could be computed simultaneously (for the purpose of the results presented in the present paper 16 cores have been used).

Fig. 1: THEA Model Structure



Source: Own illustration.

The basic steps in the dispatch and capacity expansion problem solved by THEA are presented in Fig. 1. First, the initial capacity of the power system is calculated in the master problem (MP), representing a mix of existing incumbent generation capacity as well as any new installations that are required to fulfill the power system's overall capacity requirements. Any new installations required to meet overall capacity obligations under these initial conditions are chosen based on a least cost algorithm, but initially not considering the dispatch problem. Second, this initial generation capacity mix is passed on to the dispatch part of THEA, the subproblem (SP). Here THEA solves the linear dispatch problem considering both start-up and part-load costs as well as reserve requirements. The total dispatch costs that come from the SP as well as the capacity duals are then passed on to the convergence check in the third step. Here, the algorithm measures the cost difference between the lower bound (LB) and the upper bound (UB). The lower bound is the target function of the master problem whereas the upper bound is derived from the dispatch cost of the SP and additional cost factors from the MP. Since the initial MP has only information on investment costs, and not on the inefficiency of the dispatch problem that comes from fuel, start-up and part-load costs as well as reserve requirements, there is no possibility that the algorithm can converge after only one dispatch run. Since the algorithm does not converge in the third step, in the fourth step, the full MP receives the dispatch costs as well as the capacity duals. The so called Benders' cut then calculates the change in the capacity mix that leads to a lower cost solution on the basis of the capacity duals, which are calculated in the SP and passed on to the MP. In every iteration, one additional Benders' cut is added to further constrain the solution space. This new capacity mix is then again passed on to the SP and the algorithm continues. If the solution is within the predefined cost tolerance (in this article 0.0001), the algorithm converges with the optimal solution.

3 Inputs, Scenario Definitions and Results

Input Assumptions

As mentioned earlier, this article addresses two different effects. First, the different investment decisions for the three time resolution cases are analyzed, and second, the impact of a high wind penetration on optimal capacity expansion and dispatch is compared to a case without additional wind power growth. In all instances, the model results presented here loosely simulate the power system in Texas (ERCOT, in particular), home to the largest wind power market in the United States. Except for the quantity of wind power deployed (which is input exogenously, and varies based on the two scenarios), all other inputs remain the same in the model results that follow.

Fuel prices and generation investment costs are based on EIA (2010a), whereas CO_2 price assumptions are based on Synapse (2008) (see Tab. 1 and Tab 2). Because it impacts wholesale power prices and wind energy curtailment decisions, an assumption for the $-per-kWh level of policy support offered to wind power plants is required. Based on the current production tax credit (PTC) for wind energy in the United States and on renewable energy certificate prices estimated by EIA (2007) to be needed to meet a possible future renewable portfolio standard (RPS), an incremental wind support payment of $30/MWh is assumed now and RPS certificate prices of up to $18.2/MWh in future years.

Tab. 1: Assumed Variable Cost Input Parameters

	2008	2015	2020	2025	2030
Nuclear [$/mmBtu]	0.4	0.4	0.4	0.4	0.4
Coal [$/mmBtu]	2.2	2.1	2.1	2.1	2.1
Gas [$/mmBtu]	8.9	6.3	6.6	7.0	8.0
Oil [$/barrel]	99.6	94.5	108.3	115.1	123.5
CO2 [$/t CO2]	0.0	19.5	30.8	42.1	53.4
Wind support [$/MWh]	30.0	3.9	18.2	18.2	18.2

Source: EIA (2010a), EIA (2007), Synapse (2008).

Assumed investment costs for the five alternative generation unit types considered by THEA are presented in Tab. 2 (wind is not included here, as wind power capacity is exogenously input into THEA without consideration of its costs). The "superpeaker" unit type is intended to reflect generation units that are only utilized in very few hours per year. In the modeling presented here, this unit is assumed to have the attributes of an oil turbine, though in practice, the services provided by these plants could be met with load shedding, demand-response programs, diesel generating sets, gas combustion turbines, or other options. Other generation options considered in THEA are nuclear, coal, combined-cycle gas turbines (CCGT), and open-cycle gas turbines (OCGT).

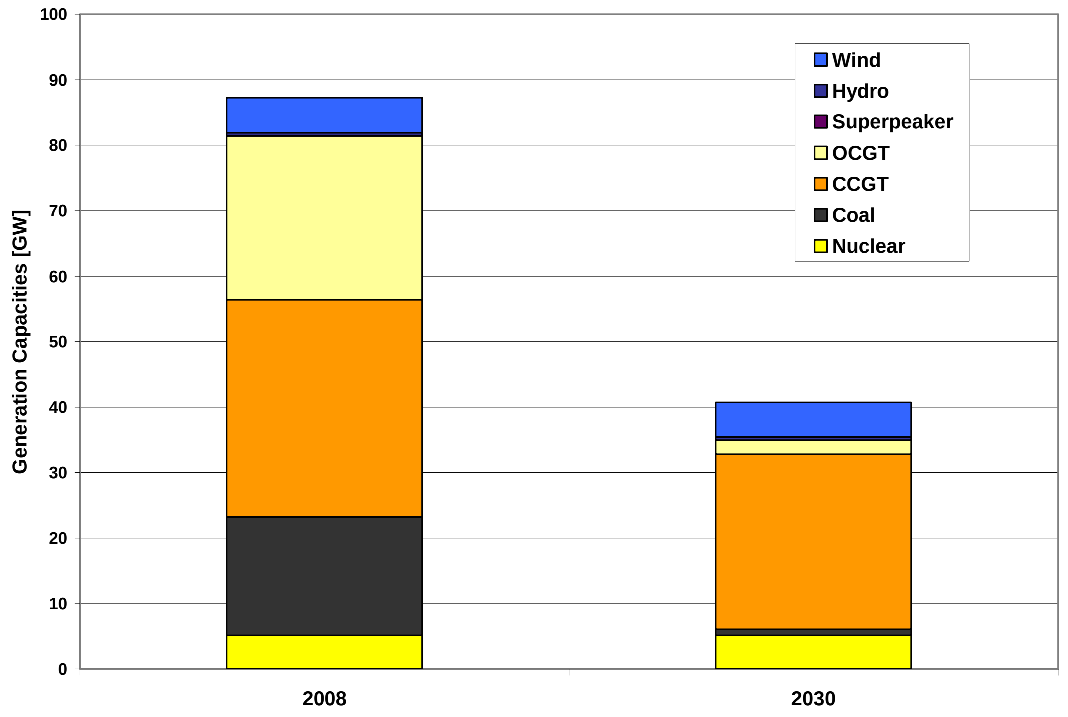
Tab. 2: Assumed Power Plant Investment Costs

	[$/kW]
Nuclear	3,820
Coal	2,223
CCGT	968
OCGT	648
Superpeaker	500

Source: EIA (2010a).

Fig. 1 shows the amount of incumbent generation capacity that is still available in 2030. With the exception of wind and hydro, the generating capacities that are required to meet the residual demand are added endogenously. The underlying lifetime assumptions for existing technologies are 50 years for nuclear plants, 40 to 50 years for coal plants, 30 to 40 years for CCGTs, 25 to 40 years for OCGTs and 40 years for the "superpeakers".

Fig. 2: Incumbent Generation Capacities



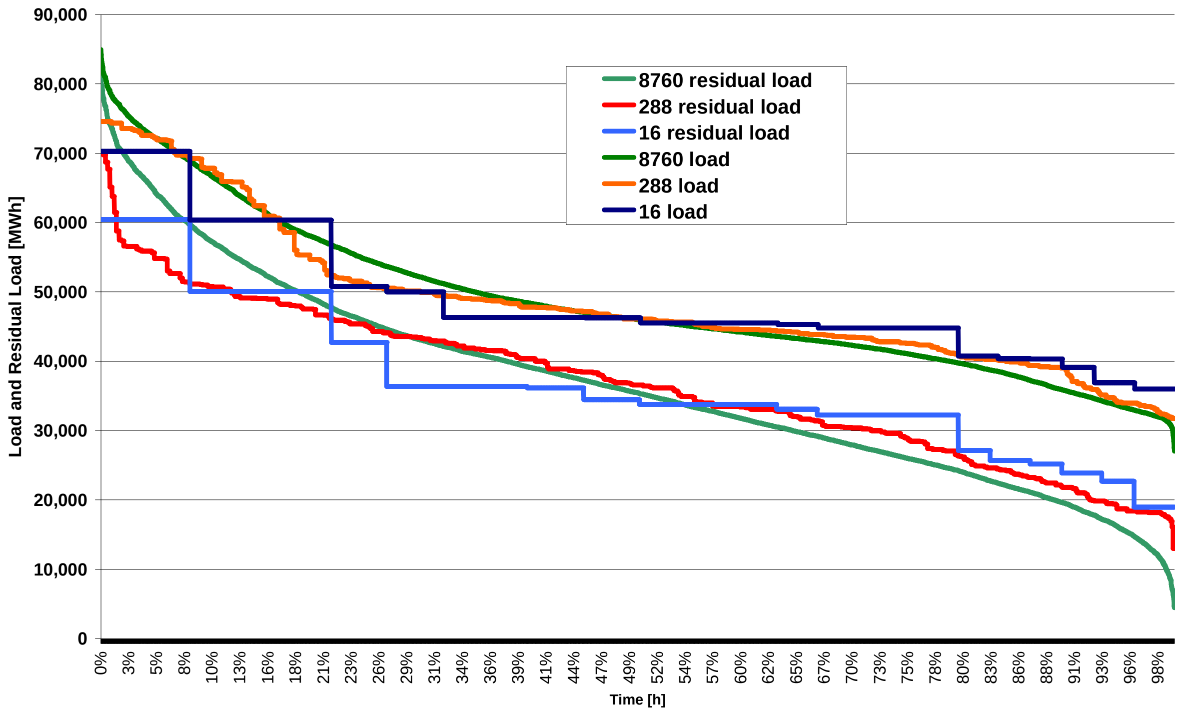
Source: own calculations, based on ERCOT (2010a) and EIA (2010b).

Overall annual electricity demand is assumed to increase from 312 TWh in 2008 to 427 TWh in 2030, which is derived from the estimated increase in peak load provided in ERCOT (2010a). The overall temporal load pattern is assumed to remain constant throughout the modeling period (ERCOT, 2010b).

In the high-wind scenario, the wind share is assumed to increase from 4.8 % in 2008 to 25 % in 2030, while in the reference scenario wind generation is kept constant at 4.8%. Since much of the new wind power deployment in the high-wind scenario is likely to occur in the western zone of the ERCOT market, away from major load centers, additional transmission capacity would be needed to serve load. Though THEA does not directly address transmission issues, it is assumed in the present analysis that new transmission is built such that in 98% of the time all wind generation is able to serve load, while during the remaining 2% curtailment is applied based on transmission limitations. This approach is consistent with ERCOT 2006), and follows the reasoning that optimal (least-cost) transmission expansion for wind will not necessarily seek to deliver each and every unit of wind electricity to load.

The initial difference in temporal resolution can be observed in Fig. 3, which shows the load duration curves for the two wind penetration scenarios under the different time slice approaches (the load duration curve for the low-wind reference case and high-wind base case are equivalent, so the only variation in the load durtation curves comes in their temporal resolution; the residential load duration curves of the low-wind and high-wind cases do differ, and Fig. 3 only presents the latter).[3] On first sight, even the load duration curve under the very low resolution case with only 16 time slices matches the 8760 h case surprisingly well. The differences between the three temporal resolutions are most obvious at both ends of the curves, but for load duration curves, are not substantial.

Fig. 3: Load and residual load duration curves for three temporal resolution cases



Source: own calculation based on ERCOT (2010b).

Since the conventional power system does not have to meet the full load, but only the residual load, Fig. 3 also highlights the three different residual load duration curves for the high wind scenario. As shown, the deviations between the three temporal-resolution cases increase with higher wind power

[3] This should be understood as one possible way to segment the time slices. This example changes if e.g. different days are selected as type-days. The approaches applied here follow dena (2005) for the type-day approach and NREL (2008) for the 16 time slice approach.

penetration. In addition to the stronger deviations, which are especially observable at both ends of the curves, the slope of the duration curves differ also to a higher degree compared to the overall load duration curves. In sum, reducing temporal resolution does not - visually – have a significant impact on the load (or residual load) curve when variable wind generation is low. At a 25% wind energy penetration level, however, the residual load curve varies substantially among the three temporal resolution cases presented in Fig. 3.

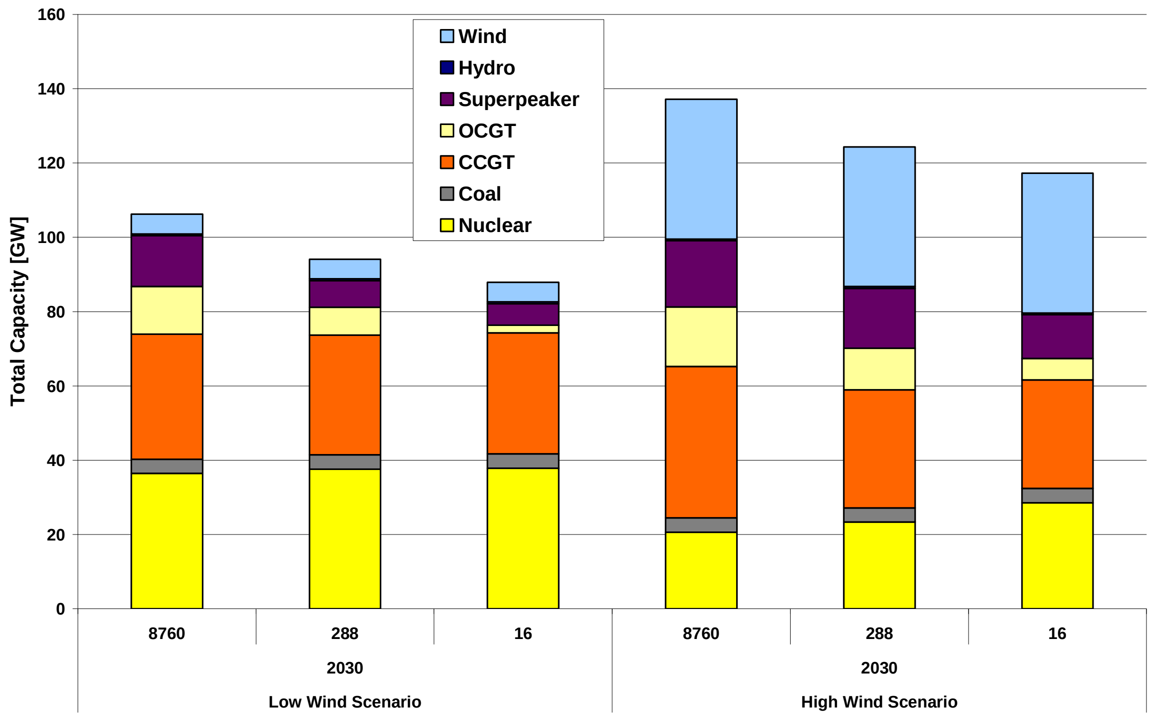
Model Results

Optimal capacity expansion

Model results for total generation capacity in 2030, by unit type, under both scenarios and all three temporal-resolution are presented in Fig. 4. In the low wind scenario, the main difference in generation capacity among the different temporal resolutions comes from different assumed peak loads. This is a direct result of the observed difference in the left-hand-side of the load duration curves shown in Fig 2, where one can see substantial differences in peak loads depending on the temporal resolution used. The higher the temporal resolution, the more effective the model is in capturing real peak load requirements, leading to greater quantities of peaking unit capacity (i.e., the capacity of "superpeakers" and the OCGTs increase as temporal resolution increases). When it comes to the remaining capacities, however, there are only slight differences among the three resolution cases in terms of nuclear, coal, and CCGT capacity.[4] Even the 16 time-slice low resolution case shows more or less the same capacity development as the high resolution case outside of the need for peaking capacity to meet hourly peak loads. Adding a "superpeak" time slice, as applied in the ReEDS model, is likely a sufficient solution to close this gap, under the low wind scenario.

[4] Note that, for all calculated scenarios, no new coal power plants are found to be built, given the CO_2 price assumptions shown in Tab. 1.

Fig. 4: Capacity in 2030 for both scenarios and three temporal resolution cases



Source: own calculations.

Optimal capacity expansion is substantially different in the high-wind penetration scenario, and also varies significantly depending on the temporal resolution. Under all three temporal resolutions, the peak capacity need under the high-wind scenario is substantially greater than under the low-penetration scenario, a capacity need that is met by substantially greater quantities of super-peakers and OCGTs, but correspondingly lower amounts of nuclear generation capacity. This shift towards greater quantities of peaking generation and lower quantities of baseload generation is consistent with other analyses of high-penetration wind energy scenarios (e.g. dena, 2005).

In comparison to the low-wind scenario, the remaining capacity mix under the high-wind scenario also varies substantially depending on the degree of temporal resolution. In addition to the greater investments in OCGTs, the higher temporal-resolution cases also result in greater investments in combined cycle gas turbines (CCGTs). When it comes to base-load general investments, even though the low resolution case has in absolute terms lower peak capacity requirements, the base-load investments are found to be higher, even in absolute terms, than in the high resolution cases. In effect, as temporal resolution increases under a high-wind penetration scenario, the remaining conventional generation mix tends to shift towards intermediate and peaking plants that can cost-effectively meet the decreased capacity factor and flexiblity needs of a high-wind scenario, while shifting away from conventional baseload units.

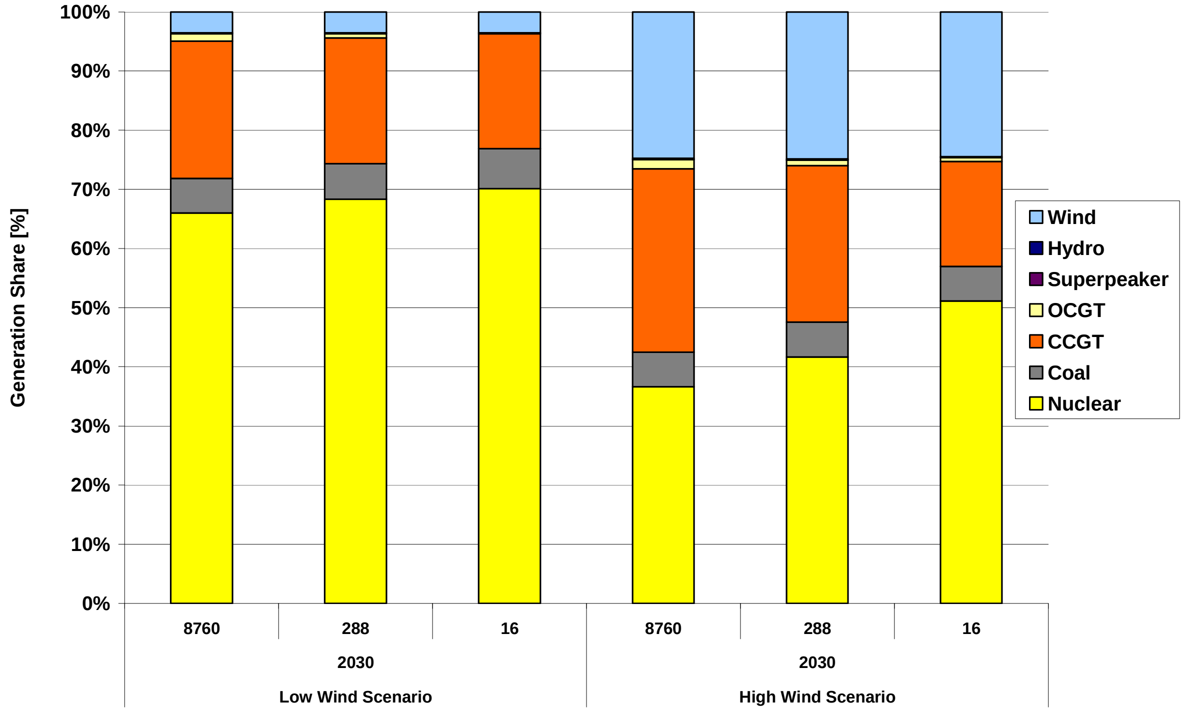
One additional outcome of this scenario comparison is the implicit capacity credit for the additional wind capacity. In 2030, the wind capacity difference between the low- and the high-wind scenarios is 32 GW. The difference in conventional capacity between the scenarios in the low resolution case is 3 GW, in the medium resolution case 2 GW, and in the high resolution case 1.4 GW, which equals a capacity credit of 9.3 % in the low, 6.4 % in the medium and 4.3 % in the high resolution case. Using lower temporal resolutions is therefore found to overstate the capacity value of wind energy.

In sum, these results demonstrate that higher temporal resolution plays a significantly more important role in high wind energy penetration scenarios than in traditional energy sector modeling. Scenarios with relatively low amount of wind energy, on the other hand, may be modeled with lower temporal resolutions without sacrificing the accuracy of the results substantially, especially if peak load requirements are accurately modeled.

Generation dispatch

Model results for generation utilization in 2030, by unit type, under both scenarios and all three temporal-resolution cases are presented in Fig 4. The generation share in the low wind scenario follows the observations above with respect to investment decisions: relatively modest differences among the temporal resolution cases. Some differences, however, are observable. Specifically, generation from nuclear plants is somewhat higher in the low resolution case, while generation from CCGTs is higher in the high resolution case. In addition, there is a small amount of generation from OCGTs in the higher resolution cases and virtually none in the low resolution case. Even with low levels of wind generation, it is clear that lower temporal resolution models are unable to fully capture the need for peaking and intermediate generation in the power sector.

Fig. 5: Generation shares in 2030 for both scenarios and three temporal resolution cases



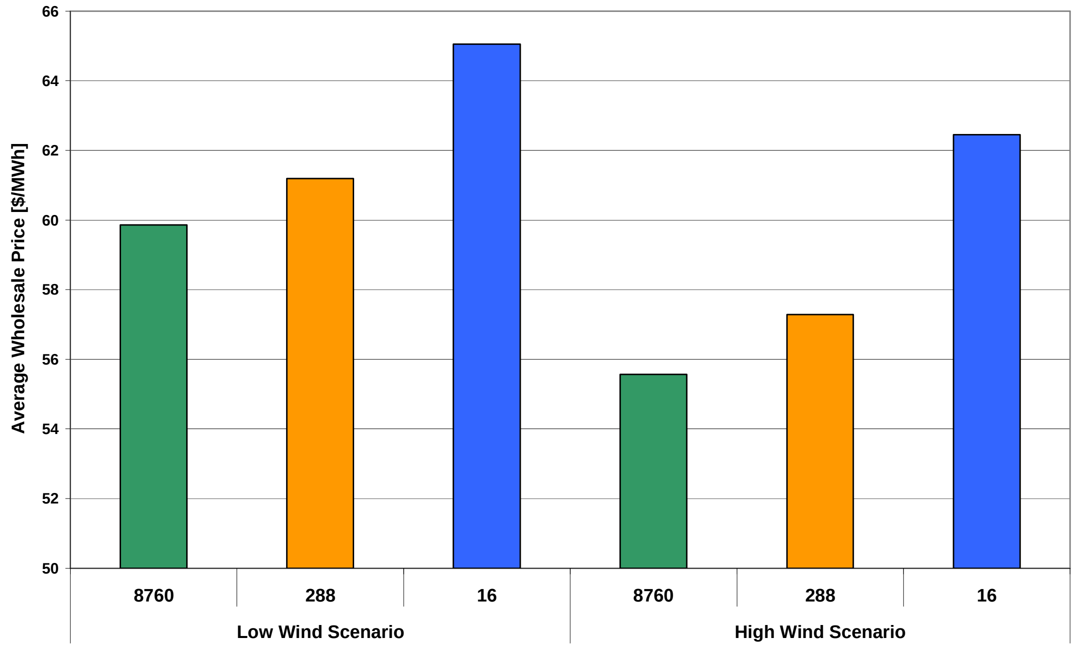
Source: own calculations.

As with the optimal capacity mix, these differences become much more striking under the high-penetration wind energy scenario. Regardless of the degree of temporal resolution, high penetrations of wind energy are found to increase the supply of peaking and intermediate generation, and reduce the need for baseload generation. Perhaps more importantly from a modeling perspective, however, is that temporal resolution has a dramatic impact on model results. In particular, the generation mix becomes much more peak oriented in the high resolution cases: there is more generation from OCGTs, CCGTs and even the "superpeaker" category has up to 21 generation hours, whereas baseload nuclear generation decreases substantially. As with capacity expansion, these results demonstrate that higher temporal resolution plays a significantly more important role in high wind energy penetration scenarios than in traditional energy sector modeling. These differences are, in part, simply an outcome of the different investment patterns, but as can be seen in the cases of OCGTs, differences are also due to dispatch decisions.

Wholesale power prices

Differences in capacity expansion and generation mix are also reflected in estimated annual average wholesale power market prices, as shown in Fig. 6. The high wind scenarios tend to have lower average wholesale prices than the low wind scenarios, while higher temporal resolutions also tend to result in lower overall average wholesale prices.

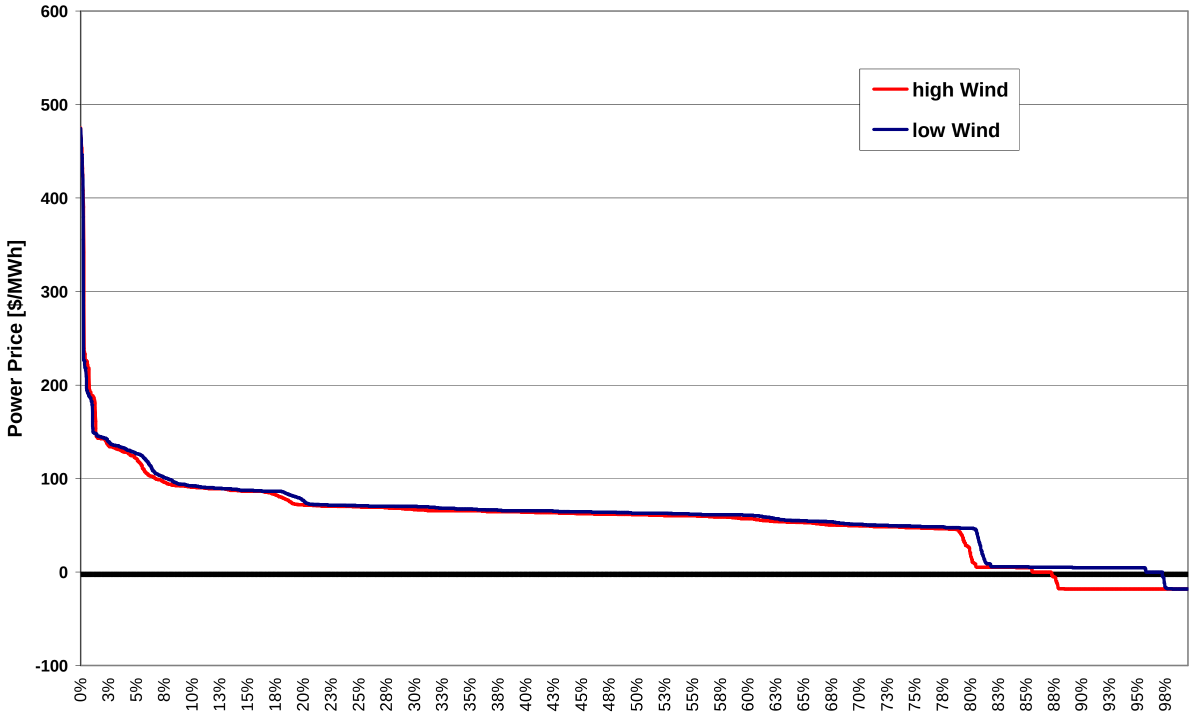
Fig. 6: Average wholesale prices in both scenarios and three temporal resolution cases in 2030



Source: own calculations.

During hours of high wind power generation, wholesale power prices are driven below the average price level, resulting in an overall reduction in average wholesale power prices under the high-wind penetration scenario, as shown in Fig. 6. Nevertheless, a second trend operates in the opposite direction: under the high-wind scenario, a greater amount of intermediate and peaking generation is used, generation that requires higher wholesale prices to support the variable costs of those units relative to baseload plants. Since the average prices shown in Fig. 6 present only the average effects, thereby masking these influences, Fig. 7 depicts the wholesale price behavior in form of price duration curves, where both of the above-mentioned trends are observable. For the purpose of Fig. 7, only the highest temporal-resolution (8760 h) cases are compared.

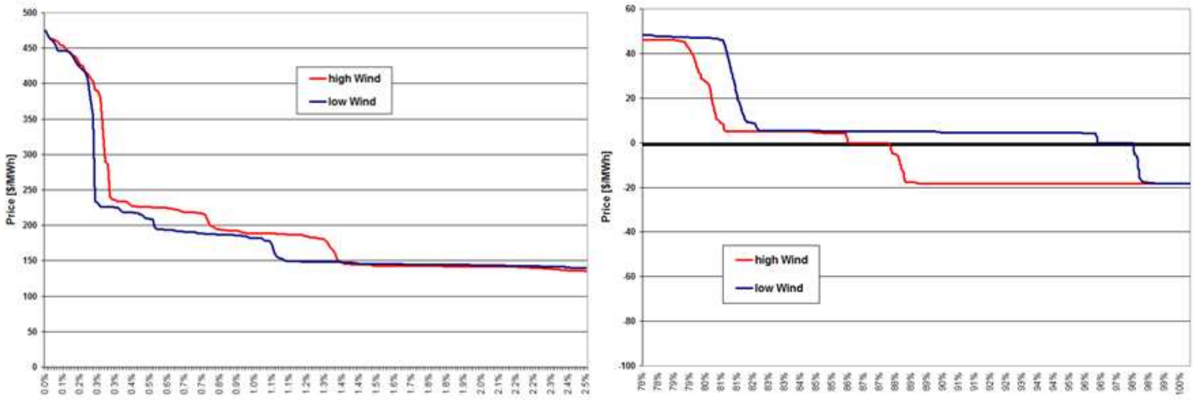
Fig. 7: Price duration curves for both 8760 scenarios



Source: own calculations.

As shown, the price duration curve of the low wind scenario is most of the time above the one from the high wind scenario, especially when prices are relatively low. During very high-priced periods, however, the opposite trend is observable. Both effects are more-readily seen in Fig. 8, which focuses on the particularly high- and low- priced portions of the price duration curve.

Fig. 8: Zoom into the highest price (left) and lowest price (right) areas



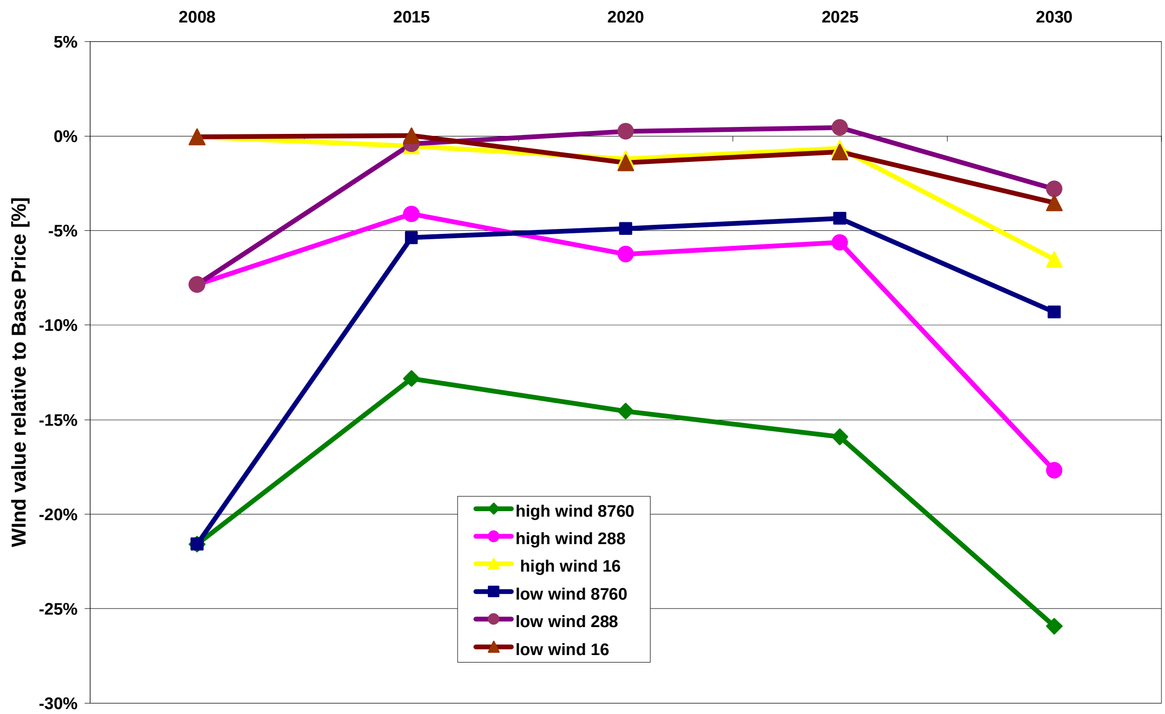
Source: own calculations.

During the periods of high wholesale power prices, the price duration curve of the high wind scenario is above the one from the low wind scenario, consistent with the higher generation share from peaking and intermediate units in this scenario and the lower use of baseload units. Though these difference in the high-price periods are relatively modest, the difference in the lowest price periods are more apparent. In particular, the price duration curve in the high wind scenario drops to low and even negative prices far more frequently than in the low wind scenario. The low, but positive plateau represents the hours in which nuclear generation represents the marginal unit, whereas negative prices are present because wind generators are assumed to receive a \$18.2/MWh support payment, so would be willing to generate at wholesale prices at or above \$-18.2/MWh. As soon as the power price drops below this \$-18.2/MWh level, wind generation is curtailed - this negative price level is therefore observable as soon as wind generation is curtailed, which of course happens more often in the high wind scenario.

Wholesale market value of wind energy

One additional metric that shows the advantage of high temporal resolution modeling and that naturally follows the price discussion is the wholesale market value of wind energy, relative to average annual wholesale prices (Fig 8). The general pattern over time shows that, after the transmission restriction is assumed to be somewhat relaxed from 2015 onwards, the wholesale market value of wind energy increases until higher wind penetration levels are reached, at which point the market value of wind drops for the reasons discussed earlier. This pattern is observable in all cases, regardless of the degree of temporal resolution, and can also be seen when comparing the low- and high-wind cases in Fig 8. In addition, the higher the temporal resolution, the lower the estimated wholesale value of wind energy since more extreme events, which are only present in the high resolution cases, have particularly strong price effects. As a result, in the low resolution case, the wholesale market value of wind is only slightly below the average wholesale price, whereas the higher resolution cases show a stronger deviation between the wholesale value of wind and average wholesale prices.

Fig. 9: Wind energy wholesale value for both scenarios and three temporal resolution cases, relative to average wholesale prices

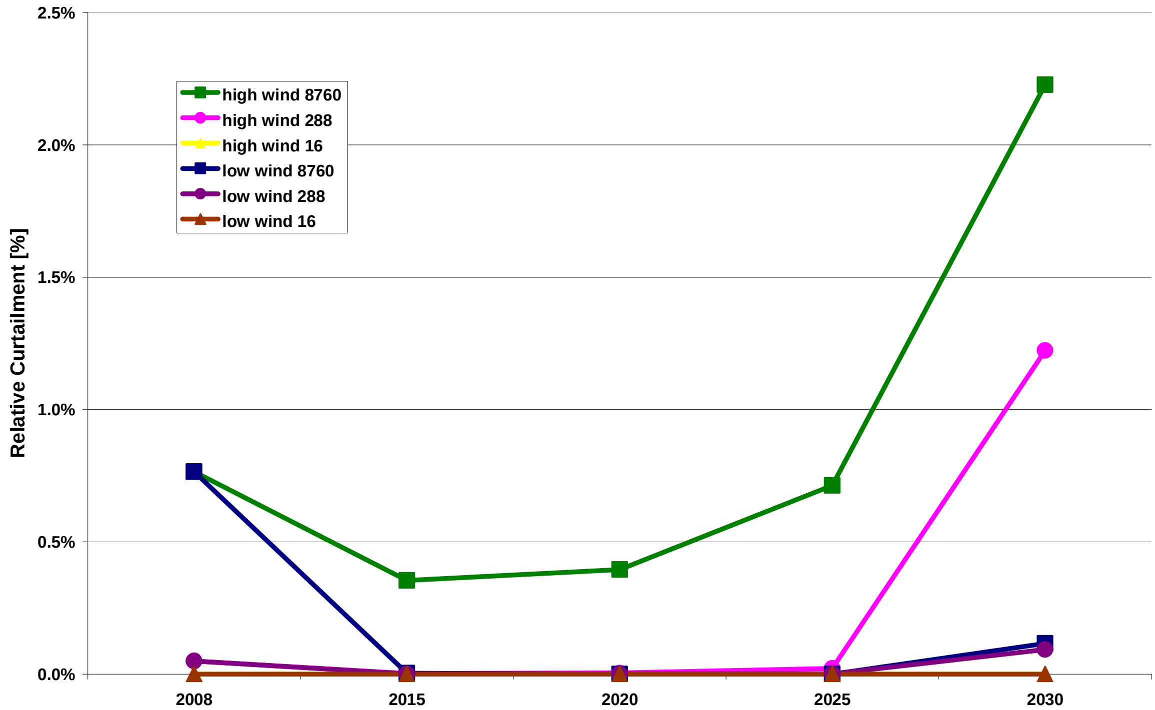


Source: own calculations.

Wind energy curtailment

Fig 9 presents model results for wind energy curtailment. Naturally, the higher wind penetration scenario also shows higher relative curtailment levels. In addition, since the extreme events only show up in the higher resolution cases, curtailment is found to increase with temporal resolution. This finding, along with the previous finding on the wholesale market value of wind energy, underline the conclusion that dispatch behavior is best matched with high temporal resolution.

Fig. 10: Relative Curtailment development in both scenarios and three temporal resolution cases



Source: own calculations.

4 Conclusion

The modeling results presented in this paper demonstrate the importance of temporal resolution in evaluating high wind penetrations. The low wind scenarios show relatively small capacity investment deviations when moving from high to low temporal resolution. The corresponding results for the high wind scenarios, on the other hand, differ significantly with temporal resolution. More specifically, under high wind scenarios, lower temporal resolutions are found to result in far-higher levels of baseload capacity (e.g. nuclear) than are found to be optimal with more accurate modeling. The higher the temporal resolution, the lower is the base load capacity. Consequently, models with low temporal resolution may substantially overstate the amount of baseload generation that would be economically optimal under a high-penetration wind energy scenario, while understating the need for peaking and intermediate generation units.

When it comes to the dispatch part of the model, temporal resolution is also found to play an important role, especially under high penetration wind energy scenarios. Again, the higher the temporal resolution, the greater the reliance on peaking and intermediate generation supply and the lower the contribution of baseload generation. Moreover, lower probability power system events are only captured when temporal resolution is high, so notable differences in the market value of wind and wind energy curtailment are observed when temporal resolution changes. The market value of wind as well as the curtailment behavior is best captured by high temporal resolution: models with low temporal resolution will tend to overstate the market value of wind, and understate the prevalence of wind curtailment.

An important implication of these results is the need to model high-wind scenarios with capacity expansion and dispatch models with high temporal resolutions. Where high temporal resolutions are not possible due to computing constraints, correction factors might instead be applied. Based on the results presented here, those corrections would ideally have the effect of reducing baseload (and increasing peaking and intermediate) capacity and generation with the level of wind energy supply, while also increasing the aggregate level of conventional capacity to meet peak system loads. In addition, in the modeling presented in this paper, wind power development was established exogenously, and the value of that wind generation was found to decrease with penetration. Though the degree of that decrease in value will depend in large measure on the composition and flexibility of the conventional generation mix, and will be highly system specific, correction factors to account for the decrease in market value of wind with penetration are needed if low temporal resolution models are used.

In conclusion, the additional requirements on the conventional power market with high wind penetration are also reflected in additional requirements for power sector dispatch and capacity expansion modeling. In general, the higher the wind penetration, the more important is the temporal resolution in simultaneous dispatch and investment decision. Fortunately, progress in computational power enables modelers to increase the degree of accuracy in the models, and increase temporal resolution. Although modeling at an hourly time step is not possible for all applications, stepwise progress seems appropriate, with correction factors applied where necessary.

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