# *VALUE OF DEMAND RESPONSE FOR WIND INTEGRATION IN DAILY POWER GENERATION SCHEDULING: UNIT COMMITMENT MODELING WITH PRICE RESPONSIVE LOAD*

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## 1. INTRODUCTION

Different operational decisions have to be made in short-term. In a time frame of eight hours to one week ahead, unit commitment modeling is applied to determine which units should be turned on and off, referred to as the plant status [1]. Generation output levels are adjusted to demand levels in order to instantaneously guarantee the system power balance. The optimization model is used to minimize generation costs, taking into account operational constraints.

Typically, fixed demand levels are included in unit commitment models. However, the expected roll-out of smart meters, allowing communication of short-term electricity prices, creates opportunities for demand-side participation. The existing models very often disregard the demand-side, assuming fixed levels of hourly electricity consumption. Consequently, opportunities for more efficient operational decision-making are neglected.

Therefore, those short-term optimization models must be improved, accounting for consumers adjusting their electricity consumption levels in response to frequently communicated electricity prices from dynamic tariff structures. Demand-side participation possibly yields load adjustments and corresponding cost reductions. Additionally, the impact of wind power variability and limited predictability may be reduced. Consequently, the positive contribution of demand response to cost reductions and wind power integration must be accounted for.

First, this paper briefly reviews how an active demand-side is currently included in unit commitment models. Then, a basic unit commitment model is described in section 3, planning the optimal commitment of generation units with fixed demand levels. Model results are used as a reference and compared to the unit commitment model with a price responsive demand-side in section 4. In section 5, the assumption of perfectly predictable wind power injections is omitted in the model by including wind power stochasticity, followed by conclusions in section 6.

# 2. MODELING ACTIVE DEMAND-SIDE IN UNIT COMMITMENT MODELS

Unit commitment models generally simplify or neglect the demand-side, when defining the optimal on-/off status and loading of power plants. However, some models include demand-side bidding, a mechanism enabling consumers to actively participate in electricity trading, typically on power exchanges. This mechanism is facilitated by consumers offering to undertake changes to their normal consumption pattern [2]. In correspondence to demand-side management, loads are rescheduled in order to balance supply and demand or to maintain system security requirements. Both household and industrial consumers can participate in demand-side bidding mechanisms. Consumers can participate directly or indirectly through a market party acting as an aggregator. The price impact of demand-side bidding is discussed in [3], where a laboratory experiment suggests reduced average electricity prices as well as reduced price volatility.

Hobbs [4] has explicitly modeled demand-side bidding in the context of a competitive electricity market. The model allows consumers to play a proactive role as they have the opportunity to submit bids for load reductions in specific hours. Those bids are directly submitted to a pool (as has been used in the Electricity Pool of England and Wales, in the 1990's as a first attempt to liberalize the electricity sector). When this load reduction bid is called upon, consumers benefit by gaining a financial reward. Although some opportunities for demand-side bidding are analyzed in [5], typically little attention is paid to the benefits with respect to the integration of non-dispatchable power integration, such as wind and solar.

An attempt to evaluate the impact of real-time pricing on the use of wind power generation in a unit commitment model is made in [6]. Consumers responding to a real-time pricing tariff increase the value of wind generation. Additionally the frequency of generation units being ramp-up-constrained or ramp-down-constrained is reduced. The impact on operational costs, such as generation, start-up, emission, and wind power curtailment costs are not mentioned.

The tendency of electrification in the transportation sector results in an additional demand for electricity. Given its characteristics, charging of electric vehicles is considered as a source of flexibility at the demand-side. The impact of plug-in hybrid electric vehicles charging is analyzed in [7]. A coordinated and uncoordinated charging approach has been applied in [8] in order to reduced energy losses and voltage deviations in a distribution grid, as well as costs for generation. No attention is paid to responsiveness to electricity price changes (price elasticity) or the welfare impact on consumers.

# 3. BASIC UNIT COMMITMENT MODEL

## 3.1 Model description

A basic unit commitment model with fixed demand levels is presented in this section used as a reference in section 4 and 5. This model optimizes the operation of power generating units in the electricity system by minimizing the operating costs and is entirely described in [9].[1] The operating costs include:

- variable generation costs
- start-up costs
- wind power curtailment costs

[1] This basic as well as the extended models are written in Matlab, calling data from Excel and use the Matlab-Gams interfacing optimization [26]. In order to solve the MILP model, Gams utilizes the IBM ILOG CPLEX Optimizer version 12.2 [27].

Both fuel and emission costs constitute the variable generation costs of generation technologies (i). Fuel Costs ($FC_i$) are expressed in €/MWh, but abstracts from partial load efficiencies, which could be included by a stepwise cost function [10]. Generation technology specific carbon emissions ($EMIS_i$) are included and multiplied by an emission price (EP). Other pollutants related to electricity generation from fossil fuels are not accounted for.

Commitment of generation units also involves a technology specific start-up cost ($SC_i$) whenever a unit is turned on. The commitment of generation units is indicated by a binary variable, which equals 1 when the unit is on and 0 when off.

Finally, excessive wind power injections in the system could result in overload situations. Clearly, those situations with excess wind power occur when the amount of wind power injected exceeds real-time power off-takes by the aggregated load. Operational constraints related to generators could already yield overload situations before the amount of wind power injections exceeds real-time system load. Network constraints can strengthen this issue [9], but are not included. Reducing hourly wind power injections in order to prevent such situations is allowed and referred to as wind power curtailment. For each MWh of wind power curtailment ($curt_u$) in hour (u), a curtailment cost (CC) is incurred.

In the basic unit commitment model, generation output meets expected electricity demand within a perimeter or control area. This real-time requirement is enforced by a system power balance, while satisfying operational constraints. System reliability requirements, such as ancillary services or reserve requirements are not included. The following operational constraints have been accounted for:

- minimum and maximum output levels
- ramping rates
- minimum up- and down-time
- start-up constraint

### 3.2 Data and assumptions

The basic model calculates the optimal unit commitment of generation units for an illustrative 48-hour period. Energy demand data is based on an hourly load profile given in the “6 bus hourly data” file, available on http://motor.ece.iit.edu/Data/. This website gathers multiple datasets used in several papers written by Shahidehpour, e.g., [11] and [12]. The wind power profile represents a realistic variability as it is based on historical data.[2] Energy demand and wind power data (Figure 1) are carefully chosen in order to include both hours with high amounts of wind power (excess wind power injections in the first six hours) as well as hours with rather moderate amounts of wind power injected. Significant flexibility is required to cope with hourly demand and wind power fluctuations. In this basic unit commitment model, only supply-side system flexibility is assumed.[3] Demand is assumed to be located in one region (single node), as well as all generation units. Also wind power is assumed to be injected into the single node system. Consequently, power injections cannot be restricted by network constraints.

Hourly wind power generation represents an aggregated profile over a control area. Injections are initially assumed to be fixed and perfectly predictable, referred to as perfect foresight. In contrast, uncertainty about actual wind power injections is accounted for in section 5. Uncertainty with respect to generation unit availability such as an unscheduled plant outage has not been considered in this paper. One single unit commitment optimization is performed in contrast to rolling unit commitment where the system is rescheduled more often given reduced wind power uncertainty over time [13].

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[2] Wind power data sets are easily accessible on the website of the Danish grid operator Energinet.dk: http://www.energinet.dk/

[3] The benefits of energy storage and interconnection capacity as sources of flexibility at the supply-side in long-term investment planning models are discussed in [28]

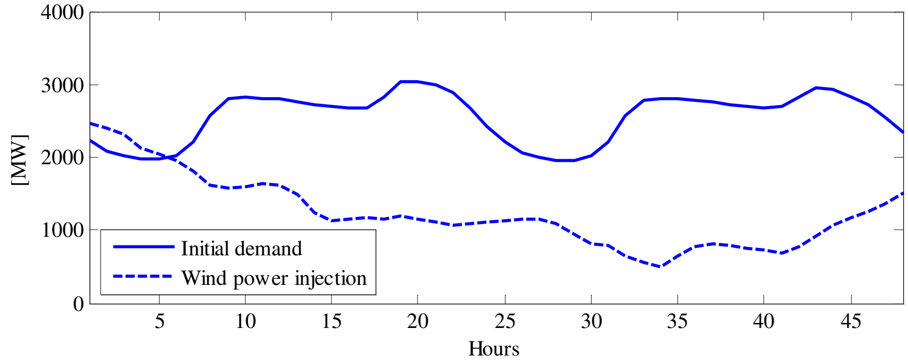


*Figure 1: Wind and demand data*

Technology-specific parameters are summarized in Table 1. Five different technologies are selected, based upon the 24-bus IEEE Reliability Test System [14] and a modified IEEE 118-bus Test System [11]. Technology-specific emissions are based on [10]. The system power plant portfolio is composed of 19 generation units. It does not represent a specific, existing region, although this could be, but serves to illustrate the model.

Two nuclear and two coal-fired power plants are assumed, as well as three CCGT plants. Nuclear power plants have the advantage of having the lowest marginal operating cost ($MC_i$), assumed to be 10 €/MWh. However, these units have the disadvantage of being less flexible, given a lower ramping rate ($RAMP_i$) and a longer minimum on- ($MO_i$) and down-time ($MD_i$) of 8 hours. Decisions taken in hour u, related to output levels or the status of a nuclear power plant, strongly influence the possible output levels or the plant status in the upcoming hours. In addition to limited flexibility from a technical perspective, starting up a base load power plant is assumed to be an expensive operation, indicated by higher start-up cost ($SC_i$) relative to peak load power plants.

Coal-fired and CCGT units typically face a shorter minimum on- and down-time. In case of a CCGT plant, once committed, it must remain turned on for only 2 hours. Correspondingly, once turned off, this plant only has to stay off for 2 hours.

Finally, six OCT plants and six GCT plants constitute the most flexible units. This characteristic is based on a minimum on- and down-time of only one hour and the ability to ramp up or down 100% of the rated capacity within one hour. OCT and GCT generation units do not have high start-up cost. In this illustrative example, they account for about 15% of the installed generation capacity, but typically operate only a limited number of hours to prevent from facing high marginal fuel costs of 110 €/MWh and 72 €/MWh respectively.

Carbon emissions are also taken into account. It must be emphasized that only marginal emissions of operating units are included, abstracting from life-cycle carbon emissions of a specific technology. Given the carbon content of the fossil fuels and an average efficiency of the available technologies, marginal emission levels (expressed in ton/MWh) are listed in Table 1. The price of carbon emissions (EP) is considered to be 10 €/ton $CO_2$.[4]

[4] The inclusion of environmental objectives such a $CO_2$ emission reduction target or different $CO_2$ prices is recommended for further research. This would be a valuable extension of the unit commitment model, illustrating fuel switching effects [29].

*Table 1: Technology-specific parameters*

| | Nuclear | Coal | CCGT | GCT | OCT |
|---|---|---|---|---|---|
| $PMAX_i$ [MW] | 400 | 300 | 250 | 30 | 30 |
| $PMIN_i$ [MW] | 100 | 100 | 75 | 5 | 10 |
| $EMIS_i$ [ton/MWh] | 0 | 0.9 | 0.41 | 0.59 | 0.78 |
| $FC_i$ [€/MWh] | 10 | 35 | 50 | 72 | 110 |
| $SC_i$ [€] | 1000 | 800 | 500 | 80 | 75 |
| $RAMP_i$ [%/h] | 33 | 40 | 50 | 100 | 100 |
| $MO_i$ [h] | 8 | 5 | 2 | 1 | 1 |
| $MD_i$ [h] | 8 | 5 | 2 | 1 | 1 |
| Number of plants | 2 | 2 | 3 | 6 | 6 |

Finally, the option of taking up not the entire hourly amount of available wind power is allowed by means of wind power curtailment. The curtailment of wind power injections can be performed at a cost of 30 €/MWh, assuming that injections are curtailed for periods of at least one hour.

### 3.3 Reference scenario

This section discusses optimal generation output levels and electricity prices for a reference scenario. This reference scenario assumes fixed demand levels and is used as a benchmark. In chapter 4, fixed demand levels are replaced by consumers able to adjust their demand levels in response to short-term prices.

The first subsection describes the method of visualizing the model outcome and discusses generation output level results; the second analyzes the model results for the basic unit commitment model with respect to the electricity price.

#### 3.3.1 Generation output level results

Optimal generation output levels are visualized as shown in Figure 2, being the reference outcome of the unit commitment model. This method of visualizing output levels is also applied later when comparing results for the extended models including demand-side flexibility. Those graphs allow better understanding of the impact of operational constraints and how the following elements are influenced:

- **Technology specific generation output**: for each hour a bar is constructed to indicate the generation output of the different generation technologies. This bar is the average hourly power output of each committed generation plant, expressed in MW as shown on the vertical axis.
- **Number of generation units committed**: the power output of each committed generation plant is indicated by a coloured bar. By encircling the plant specific output in black, the number of generation units which are committed can be counted.
- **Aggregated energy demand**: the sum of hourly conventional power generation and net wind power injection equals the aggregated energy demand. It is indicated by the full bold line above the wind power bar and below the coloured bars indicating partial plant loading.
- **Full or partial plant loading**: partial plant loading occurs when a generation plant is committed, but not operating at its rated capacity. In that case, the amount of unused capacity is shown by a colored bar above the aggregated energy demand curve.[5]
- **Amount of wind power curtailment**: the amount of wind injections being curtailed in a certain hour is displayed by the dashed line and indicated as a negative value as the amount of wind power injected is negatively impacted.

[5] Colored bars indicated above the aggregated demand curve may not be interpreted as spinning reserves, because the availability of those residual capacities may be restricted by operational constraints such as ramping rate limits. Spinning reserves, providing upward and downward flexibility, can be calculated after the unit commitment optimization, but are not the focus of this paper.

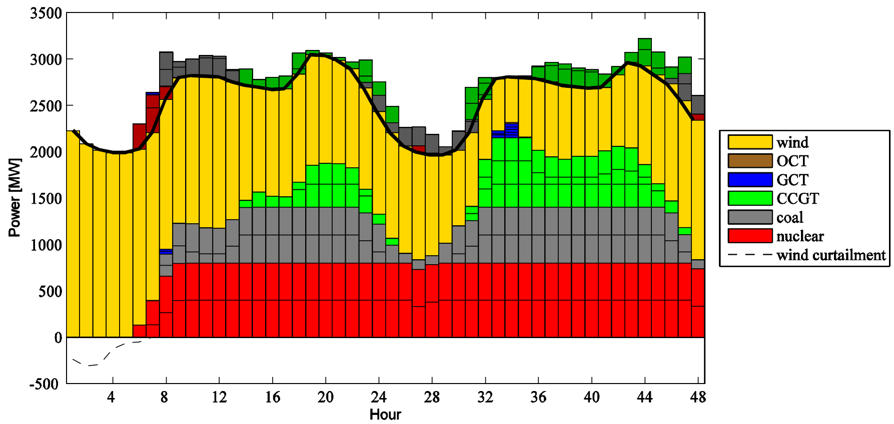


*Figure 2: Generation output levels: basic unit commitment model without demand-side flexibility*

In the basic unit commitment model without demand-side flexibility, the first nuclear power plant is turned on in hour 6 and the second nuclear power plant in hour 7. Partial loading of those units is shown by the red bars above the aggregated energy demand curve in Figure 2. Given restricted flexibility this unused capacity is not yet available for power generation. It takes at least three hours before those nuclear power plants reach rated capacity as enforced by the 33% ramping limit.

The two coal-fired power plants are turned on in hour 8 and restricted by their 40% ramping limit. The power output of the nuclear and the coal-fired power plants, combined with the wind power injection is deficient to satisfy energy demand in hour 8. Two additional GCT plants must be turned on in order to ensure the system power balance. A first and second CCGT plant are turned on in hour 14 and 18 respectively, in response to peaking demand levels. Even though the demand peak is less pronounced between hours 32 and 36 compared to hour 20, net demand levels, after subtracting wind power, are higher. The third CCGT plant, five GCT plants and even one OCT plant must be turned on as a result of a much lower amount of wind power injected.

Finally, generation output levels in hour 27 and 28 also require special attention. Reduced conventional energy demand levels during the night cause one coal-fired plant to be turned off. It takes five hours before this plant can be turned on again, as enforced by the minimum down time constraints. At the same time, the output of the other coal-fired power plant is reduced to the minimum level of 100 MW. Also the output of the nuclear power plant is slightly reduced. Again, unused capacity of the nuclear and the coal-fired power plant are shown above the aggregated demand curve, corresponding to the partial load levels.

Figure 2 shows that wind power is curtailed from hour 1 until hour 6. Curtailment levels up to about 300 MW in hour 2 can be seen in order to ensure the system power balance. It must be noticed that wind power curtailment also occurs in hour 6, even though the first nuclear power plant is already turned on.

### 3.3.2 Electricity price results

The real-time price of electricity (RTP) for the basic unit commitment model (Figure 2) is displayed by the full line in Figure 3. The coal-fired power plant is the marginal generation plant from hour 9 until 14 and from hour 29 until 31. The marginal fuel costs of a coal-fired power plant are assumed to be 35 €/MWh. An emissions level of 0.9 ton $CO_2$/MWh generated, multiplied by a 10 €/ton $CO_2$ emission price, amounts to a cost of emissions equal to 9 €/MWh. The combined marginal cost of generation yields an electricity price equal to 44 €/MWh (Figure 3).

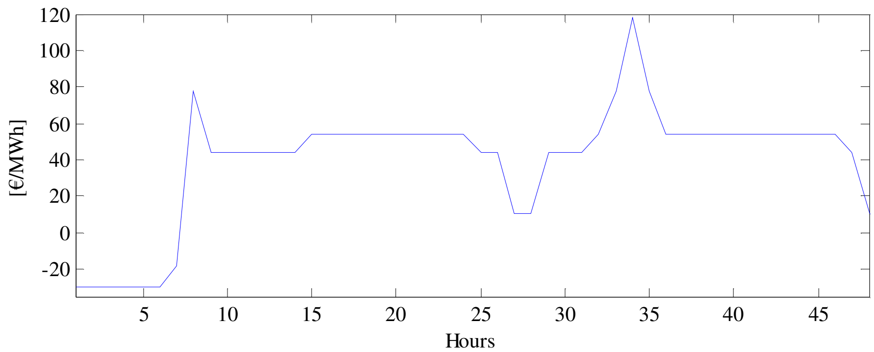


*Figure 3: Real-time price of electricity: basic unit commitment model*

The CCGT plant is the marginal generation plant from hour 15 until 24 and from hour 36 until 46. The marginal fuel costs of a CCGT plant are assumed to be 50 €/MWh. An emissions level of 0.41 ton of $CO_2$/MWh generated, multiplied by a 10 €/ton $CO_2$ emissions price, amounts to a cost of emissions equal to 4.1 €/MWh. The combined marginal cost of generation yields an electricity price equal to 54.1 €/MWh (Figure 3). Correspondingly, the electricity price can be calculated for those hours when the GCT and the OCT are the marginal generation plant, resulting in electricity prices of 77.9 €/MWh (hour 8, 33 and 35) and 117.8 €/MWh (hour 34). During hours of wind power curtailment, the price of electricity becomes negative, because increasing electricity demand by one MWh reduces curtailment costs by 30 €/MWh. The weighted average electricity price over this 48 hour period equals 42.7 €/MWh.

# 4. PRICE-BASED DEMAND RESPONSE IN UNIT COMMITMENT MODEL

Unit commitment models with fixed demand profiles pursue the reduction of system costs. However, with the expected roll-out of smart metering appliances, consumers can take the decision to adjust their initial demand levels in response to price changes, referred to as price-based demand response. When short-term demand response is integrated, fixed demand profiles are replaced by hourly elastic demand functions [15]. The model must define a solution characterized by an equilibrium price and demand for each hour, in accordance with Samuelson's principle [16]. The price-quantity market equilibrium is equivalent to maximizing the sum of producer and consumer surplus. Consequently, the solution maximizes welfare, being the integral of the demand function, at a minimum cost for generators taking the operational constraints into account. According to microeconomic theory, consumer surplus maximizing end-users increase their demand up the point where the cost of consumption is equal to the marginal benefits obtained from the consumption [17]. The welfare gained by consuming one additional amount of energy would be lower than the price to be paid for this additional amount of energy. Correspondingly, the loss of consumer surplus after reducing the level of consumption compared to equilibrium demand would be larger than the savings of reduced consumption.

## 4.1 Model extension

First, the unit commitment model is optimized for the 48-hour time period with fixed demand levels and given the parameters described in subsection 3.2. The model output defines the optimal commitment of the available generation units subject to the operational constraints. Based on the dual variable or shadow price of the nodal energy balance requirement the marginal price of electricity is found. This marginal price is then used to calculate a weighted average energy price. This is the flat tariff currently faced by consumers as they are assumed not to be under a real-time pricing structure.[6] The single tariff combined with the fixed hourly demand level constitutes an equilibrium and is used as an anchor point through which the linear elastic demand function is drawn. Own-price elasticities are included, resulting in hourly short-term demand response. Changing the elasticity corresponds to adjusting the responsiveness of consumers with respect to price changes.

The equilibrium solution considering short-term demand response represented by the linear elastic demand function can be found by reformulating the Mixed Integer Linear Program (MILP) model as a mixed integer nonlinear problem [18]. As these models are typically hard to solve, an alternative computational procedure is suggested in [15] given current supply characteristics and a piecewise linearization of the price elastic demand function.

Still, perfect foresight is assumed, meaning the real-time wind power injections as well as consumers' demand and their responsiveness to electricity prices is perfectly know in advance. As nothing changes between day-ahead when the optimal commitment is defined and real-time, the expected hourly prices are equal to the real-time price levels.

## 4.2 Model results

This subsection illustrates the impact of integrating short-term price-based demand response into the basic unit commitment model focusing is on generation output levels, electricity prices, as well as on operational costs and environmental benefits.

### 4.2.1 Generation output levels

Figure 4 shows the generation output levels given different levels of own-price elasticity, respectively -0.10, -0.20 and -0.30. A higher absolute value of own-price elasticity corresponds to higher demand-side flexibility, yielding higher demand adjustments. Looking at the first 8-hour period, demand levels are increased by about 500 MW or 20% when compared to the initial load profile in the -0.30 own elasticity scenario. Simultaneously, initial peak load levels are reduced by almost 300 MW or 10% between hour 18 and 22. The amount of load adjustment is less pronounced for a -0.10 own-price elasticity scenario. Demand-side flexibility only yields a valley filling effect of about 300 MW in the first 3 hours, and only 150 MW between hour 4 and 6 in the -0.10 own-price elasticity scenario.

Valley filling effects during the first hours of this period allow an earlier start-up of the nuclear power plants. In the -0.30 own-price elasticity scenario, one nuclear power plant is on during the entire 48-hour period. Valley filling effects also occur during the off-peak period between the first and the second 24-hour period, especially around hour 27 and 28. The increased generation output levels of the nuclear power plant also increase its capacity factor, which is the ratio of the total energy generated by a generating unit for a specified period (in this case 48 hours) to the maximum possible energy it could have generated if operated at its maximum rated capacity (Figure 5) [19].

CCGT power plants are typically used to satisfy demand for electricity during peak load. Generation output levels of the CCGT plant are reduced when increasing the demand-side flexibility. When assuming only -0.10 own-price elasticity, generation output levels are only slightly reduced between hour 15 and 22. When assuming higher absolute levels of own-price elasticity, the starting up of the first CCGT plant can be delayed until hour 18. Furthermore, it is not required to turn on a second CCGT plant in the first 24-hour period.

[6] A similar methodology could be applied to calculate weighted average prices for a double tariff structure, with peak and off-peak periods [30].

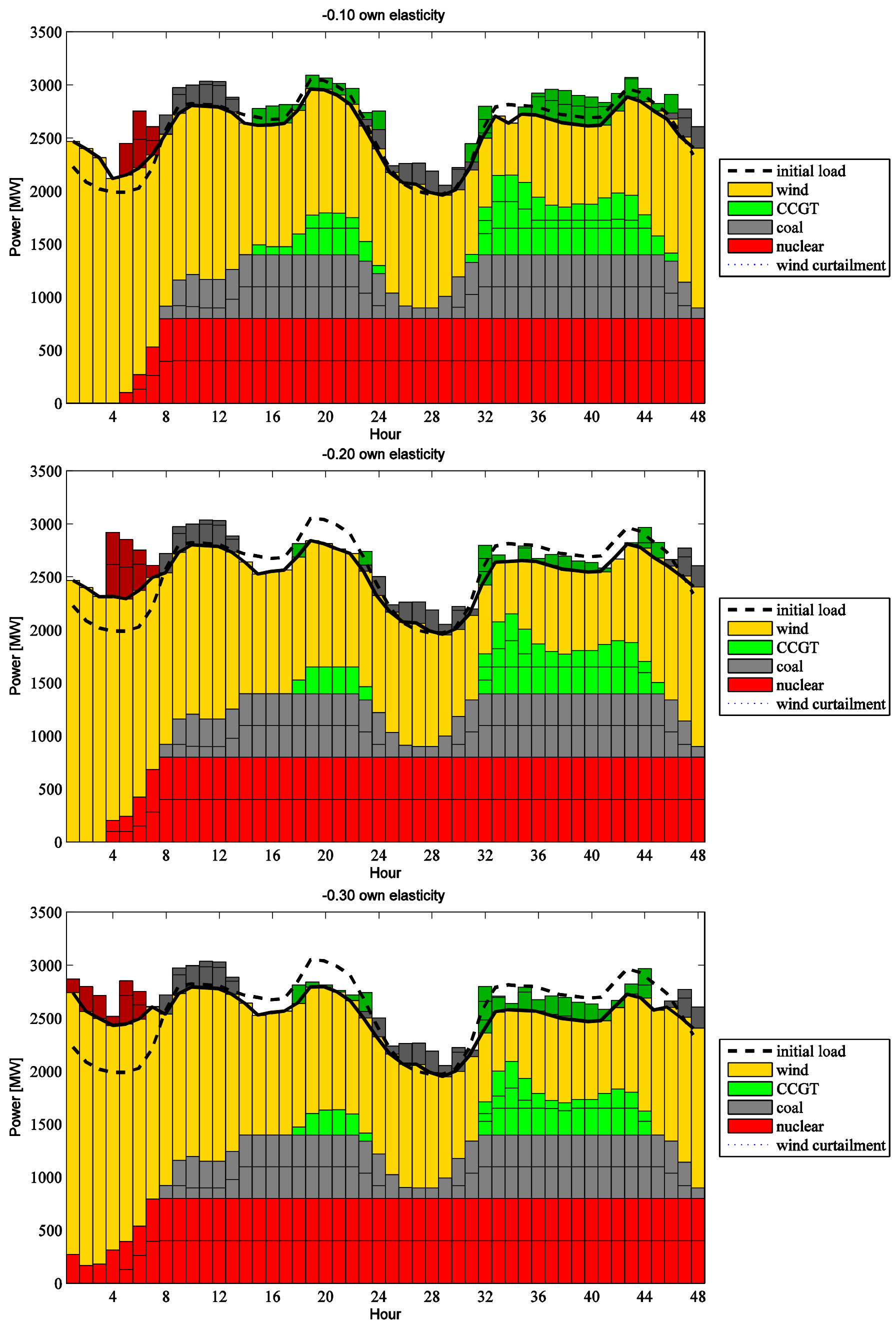


*Figure 4: Generation output levels: unit commitment with price-based demand response*

Initial load levels are also reduced during the peak load period from hour 32 until 44. When reducing the demand-side flexibility with own-price elasticity levels from -0.30 to -0.20 and -0.10, initial load levels are reduced by more than 200 MW, about 150 MW and little less than 100 MW, respectively. As a result, not only the CCGT generation output levels are reduced, but also the third CCGT plant can be switched off after hour 35 when assuming -0.20 or -0.30 own-price elasticity levels. This result is also proven by a reduced capacity factor for the CCGT plants (Figure 5).

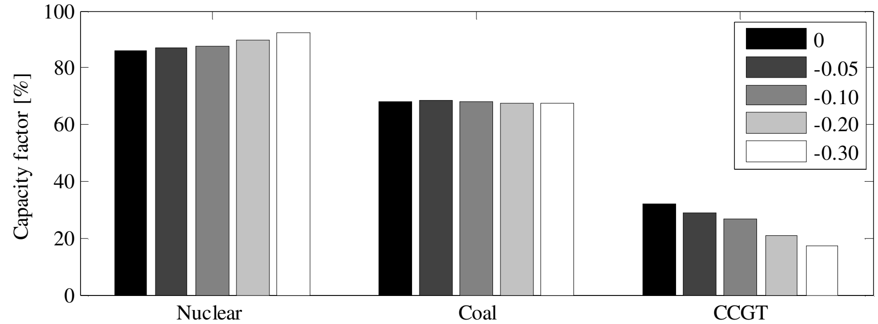


*Figure 5: Capacity factor for nuclear, coal-fired and CCGT power plants*

### 4.2.2 Electricity prices

So far, no attention is paid to the driver behind demand-side response, being the hourly electricity price. The initial flat tariff price of 42.7 €/MWh is calculated as the weighted average electricity price for the basic unit commitment model without demand response. Market clearing hourly electricity prices for the different scenarios with demand-side flexibility must be compared to the flat tariff in Figure 6. All deviations of the hourly electricity price from the flat tariff explain load changes. The larger the price difference between the real-time electricity price and the flat tariff, the larger demand adjustment. This applies for both up- and downward price differences.

Upward price spikes typically occur at moments of high demand levels or load fluctuations. GCT and OCT power plants are able to deal with such situations and finally help to meet real-time electricity demand. Since these units have higher marginal operational costs, price levels increase. On the other hand, downward price spikes typically occur at moments with a large amount of wind power.[7] Excess wind power injections are curtailed, enforcing curtailment costs. During moments of excess wind power supply before hour 8, lower electricity prices make consumers increase initial demand levels. Finally, also moments occur with market clearing prices negligibly deviating from the flat tariff, such as between hour 10 and 13, or around hour 30. Then, the aggregated demand levels almost perfectly match the load levels.

Consumers' response to price changes finally reduces the frequency and the size of the price deviations. Consequently, electricity price volatility measured as the standard deviation is significantly reduced (Figure 7). Assuming only -0.05 own-price elasticity, already decreases price volatility for this period from 30 to 25 €/MWh. Assuming a higher demand-side flexibility of -0.20 reduces price volatility further by half to about 15 €/MWh.

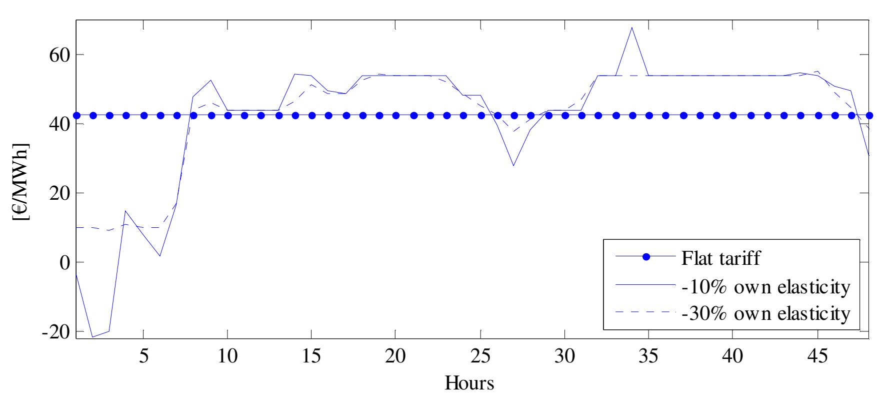


*Figure 6: Real-time price of electricity: unit commitment model with price-based demand response*

[7] The concept of downward price spikes on power exchanges is mentioned in [31].

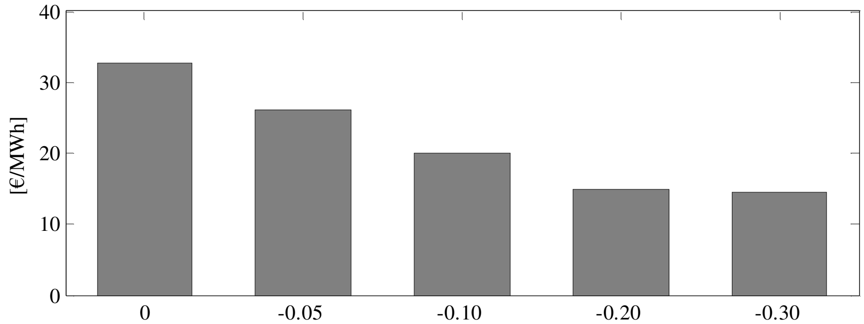


*Figure 7: Electricity price volatility (standard deviation) assuming different levels of own-price elasticity*

#### 4.2.3 Operational costs

Price-based demand response also impacts operational costs (Table 2). Increasing the assumed level of own-price elasticity from -0.05 to -0.30 helps reducing total operational costs by approximately 10% to 20% in this 48-hour period. Price-based demand response has a similar effect on both generation and start-up costs.

*Table 2: Operational costs and environmental benefits: price-based demand response*

| Own elasticity | Total costs [€] | Generation costs [€] | Start-up costs [€] | Emissions [ton] | Curtailment [MW] |
|---|---|---|---|---|---|
| -0.00 | 1.889.414 | 1.623.726 | 7.514 | 22.526 | 1.097 |
| -0.05 | 1.790.374 | 1.554.166 | 7.044 | 21.981 | 312 |
| -0.10 | 1.733.157 | 1.511.221 | 6.900 | 21.504 | 0 |
| -0.20 | 1.624.976 | 1.412.454 | 6.400 | 20.612 | 0 |
| -0.30 | 1.564.771 | 1.357.991 | 6.400 | 20.038 | 0 |

#### 4.2.4 Environmental benefits

The inclusion of price-based demand response into a unit commitment model also has environmental benefits. In this example, responsive consumers realize $CO_2$ emission reductions between 5 and 10% of the initial carbon emission levels. Most notable is the impact on the amount of wind power curtailment. Price-responsive consumers increase electricity demand compared to initial demand levels. Even given -0.10 own-price elasticity, the total amount of available wind power can be consumed and no wind power is curtailed.

# 5. PRICE-BASED DEMAND RESPONSE IN UNIT COMMITMENT MODEL WITH WIND POWER STOCHASTICITY

## 5.1 Impact of wind power uncertainty

Wind power injections have to be forecasted to define the residual amount of power that needs to be generated by conventional plants. Forecasting errors entail additional system cost, whereas improving wind power predictions has a significant economic benefit, measured as fuel savings from conventional units in [20]. Given an underestimation of the wind power injections in a control area, downward reserve power is required to ensure the power system balance. Generation flexibility prevents overcommitment of conventional units, when the amount of wind power injected turns out to be higher in real-time.

Correspondingly, given an overestimation of the wind power injections in a control area, upward reserve power is required [21]. In that case, generation flexibility must prevent undercommitment of conventional units, when the amount of wind power injected turns out to be lower in real-time. When too little generation flexibility is available, the adequacy of the power system is at risk as the probability of failure increases. Alternatively, system costs are increased above optimal operational levels when too much flexible generation capacity is kept available [22].

This section abstracts for the presumption of perfectly predictable wind power injections. The basic unit commitment model is extended in order to quantify how price responsive consumers react in scenarios with forecast errors. These forecast errors result from stochasticity of real-time wind power injections. Depending on the hourly amount of wind power injection, a different price is send to the consumers, resulting in scenario specific levels of hourly electricity demand.

## 5.2 Model extension

Wind power uncertainty is now included into the unit commitment model with price-based demand response, assuming different real-time wind power injection scenarios. Equilibrium price and demand levels are defined for each hour in every scenario. Consequently, this model indicates the ability to deal with forecasting errors at a minimum cost.

Uncertainty about the real-time wind power injection in the system is included by constructing a stochastic mixed-integer linear programming (MILP) model. The stochastic part is presented by a scenario tree for possible wind power generation forecasts for each individual hour [23].

**Scenario-specific parameters**
The inclusion of stochasticity has model implications. Partitioning of scenario-specific parameters as well as scenario-specific decision variables must be done [24]. Hourly wind power injections become scenario-specific, where each scenario has a predefined hourly probability of occurrence.

The number of scenarios, as well as the deviations between different possible wind power injections can be based on standard deviations of wind power forecasting errors and the forecast lag [25]. Three different scenarios are assumed with an equal probability of 33.3% designated to each scenario:

- Scen 1: Wind power overestimation: 25% less wind power injected in real-time
- Scen 2: Wind power correctly forecasted
- Scen 3: Wind power underestimation: 25% extra wind power injected in real-time

The amount of over- or underestimation of wind power injection is indicated by an hourly, scenario-specific relative parameter. This value of over- and underestimation is assumed to be each 25%. Scenario 2 corresponds to a correct wind power forecast.

**Scenario-specific decision variables**
Several decision variables must be partitioned in response to different wind power injection scenarios. The unit commitment model without wind power uncertainty already entailed wind power curtailment during periods of excessive wind power injections. A different optimal amount of wind power curtailment is allowed given different wind power scenarios.

After subtracting from different levels of wind power injection, different net load levels are found, which must be satisfied by the conventional generation output. Each generation plant has a scenario-specific hourly output level. Generation output deviations in each of the scenarios relative to scenario 2 in the previous hour satisfy the ramping rate constraints.

Nuclear, coal-fired and CCGT plants have a technology specific minimum on- and down-time. Therefore, those conventional generators are not turned on or off, depending on the scenario, in order to supply electricity demand. The on or off status of these units is assumed to be fixed in each scenario for a given hour. The 0-1 binary variable indicating the plant status is not partitioned for scenarios for those units. However, the on or off status of the more flexible GCT or OCT plants can be more easily adjusted. As a consequence, a scenario depending 0-1 binary variable indicating the plant status is included, specifically for those units. The scenario-specific plant status variable for high peaking units also requires a scenario-specific start-up cost.

Different output levels of committed generators or even different levels of wind power curtailment may finally impact price levels. Hourly, scenario-specific electricity prices are equal to the dual (shadow price) of the system power balance requirement. Assuming price-based demand response, scenario specific price levels finally yield scenario-specific hourly electricity demand.

## 5.3 Model results

The introduction of price-based demand response in the unit commitment model with wind power stochasticity impacts the optimal generation output levels and the corresponding market clearing equilibrium prices. Furthermore, operational costs and environmental benefits for the scenario with and without price-based demand response are compared.

### 5.3.1 Generation output levels

Generation output levels are gathered in Figure 8 in order to illustrate the impact of demand-side flexibility, accounting for three real-time wind power injection scenarios. On the left-hand side, the optimal output levels of three scenarios are shown without price-based demand response. On the right-hand side, the three graphs show optimal output levels for the same scenarios, while price-based demand response is included, assuming a -0.15 own-price elasticity.

**Correct forecast**

Starting from the second scenario (second row of graphs), generation output levels are presented given a correct wind power forecast. It is assumed that this situation occurs with a probability of 33.3%. The output levels without demand response differ markedly from the situation without wind power uncertainty (Figure 2).

The first nuclear plant is already operating in hour 1 above the minimum run level of 100 MW. In order to balance generation and demand, 150 MW of wind power is additionally curtailed, increasing optimal wind power curtailment levels up to 460 MW in hour 2. Nuclear power plants are much longer fluctuating on partial load levels. They only reach rated power output levels in hour 13, instead of hour 9 without wind power uncertainty. The start-up of the first CCGT power plants is also advanced from hour 14 to hour 8. Even a third CCGT plant is turned on between hour 18 and 22, which does not occur without wind power uncertainty. Similar to nuclear power plants, committed CCGT plants are operating at lower output levels, but offer upward flexibility which is required in scenario 1 with overestimated wind power injections.

Including demand response in the correct wind power forecast scenario, yields increased demand levels by up to 500 MW in the first hours, avoiding excess wind power injections. During the other hours, initial demand levels are less significantly impacted. The demand profile after response rarely deviates more than 100 MW from the initial levels. Despite those little demand adjustments, the optimal generation output profile presents less partial loading.

The scenario with a correct wind power forecast must be compared to the scenarios where real-time wind power injections are over- or underestimated.

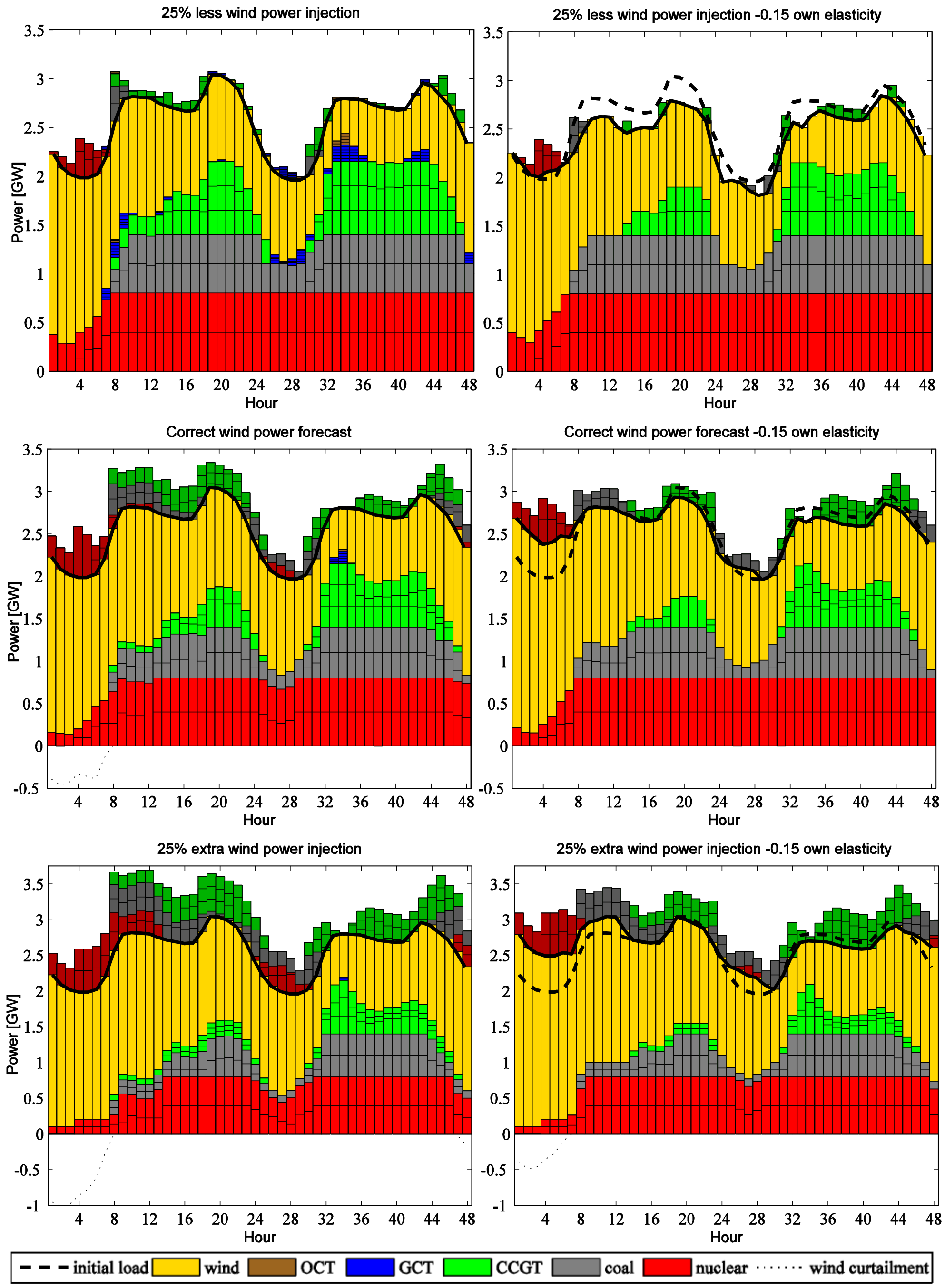


*Figure 8: Generation output levels with wind power uncertainty*

**Wind power overestimation**

The first scenario (first row of graphs) represents a forecasting error where the amount of wind power injected is overestimated. In real-time 25% less wind power is injected. This deficit must be offset by increased conventional power generation output levels.

Without demand response (upper left graph), output levels of nuclear power plants increase in the first 6 hours. Coal-fired power plants raise output levels from hour 8 until 18 and from hour 23 until 30. Also CCGT power plants are able to ramp up during moments of overestimated wind power injections.

Further, in several hours, GCT power plants are additionally turned on. Finally, in hour 8, 33 and 34 OCT plants even have to be started-up to provide sufficient flexibility.

When consumers respond to real-time price signals, demand is adjusted compared to the initial demand levels (dashed line in upper right graph) when less wind power is injected in real-time. During peak, as well as off-peak period initial demand levels are lowered by 100 MW up to 250 MW. Demand adjustments even reach a reduction of about 340 MW in hour 9. By reducing demand levels, GCT and OCT power generation can be avoided

**Wind power underestimation**
The third scenario (third row of graphs) represents a forecasting error where the amount of wind power injected was underestimated. In real-time 25% extra wind power is injected. This surplus of power injection must be offset by lowering conventional power generation output levels.

Without demand response (lower graph left), nuclear power plants are still operating at minimum run levels of 100 MW from hour 1 until 7. Since these plants are turned on, it is technically not possible to turn them off. As a consequence, wind power injections are heavily curtailed, even up to 1000 MW in hour 2, in order to ensure the real-time system power balance. Between hour 8 and 13, the output of the coal-fired power plants is reduced to the minimum run level when real-time wind power injection turn out to be 25 % higher than initially forecasted. Again, it is technically not possible to turn off these plants. Output levels of all CCGT plants which have been turned on between hour 8 and 25 are also lowered to the minimum output level of 75 MW.

When consumers response to real-time price signals, demand is adjusted, compared to the initial demand levels (dashed line in lower right graph), when 25% extra wind power is injected in real-time. In the first 13 hours, initial demand levels are raised. In the first 8 hours, this results in a higher uptake of available wind power. Demand-responsive consumers make that hourly wind power curtailment levels are more than halved. Between hour 9 and 13, demand-responsive consumers make that nuclear power plant can operate at rated output levels, in contrast to a situation without demand response.

### 5.3.2 Electricity prices

Given different wind power forecasting scenarios, electricity prices are listed in Figure 9. Electricity prices in the upper graph without demand response can be explained by the marginal cost of generating electricity, as discussed before. Price profiles are shown as if each scenario would occur for the entire period of 48 hours.

Depending on the scenario and the hour, a different generation plant may be the marginal unit, resulting in different electricity prices. Price levels are commonly higher when less wind power is injected and lower when extra wind power is injected, compared to the correct forecasting scenario. The current generation portfolio is insufficient to satisfy demand in hour 34 in scenario 1. An additional back-up GCT plant is added to the model with marginal fuel costs of 150 €/MWh and comparable minimum run, ramping and emission characteristics. The peak demand level in hour 34 causes a price spike up to 155,9 €/MWh, after accounting for emission costs.

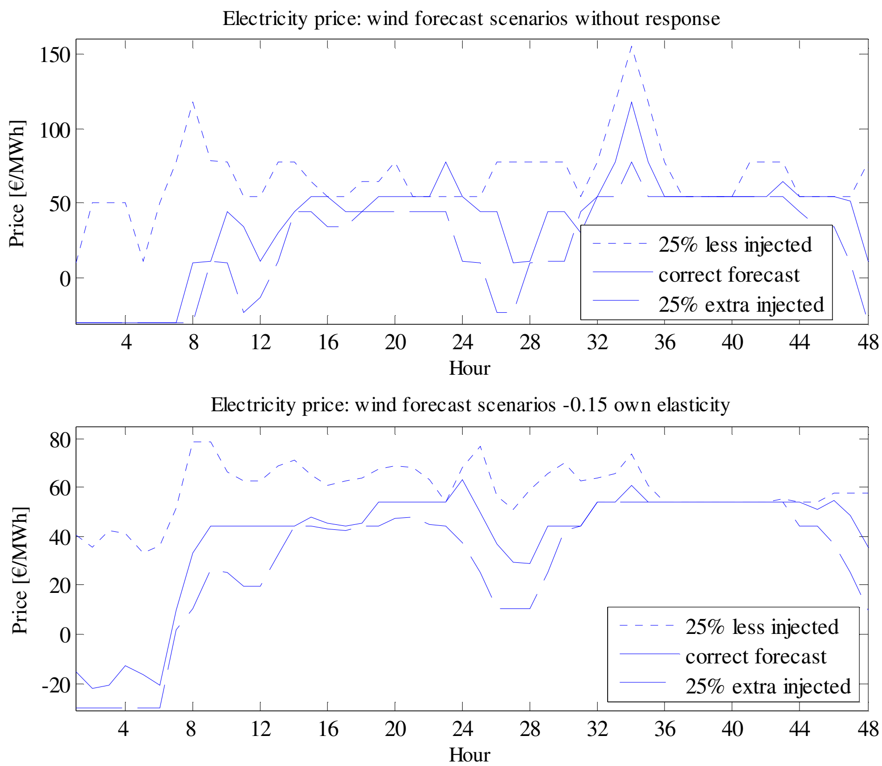


*Figure 9: Electricity prices with wind power uncertainty: with and without price elastic demand*

After including price-based demand response into the model, higher market equilibrium electricity price levels can be found when less wind power is injected. Correspondingly, lower price levels can be found when extra wind power is injected. The deviation between price levels for the correct forecast scenario and the other two scenarios is reduced when price-based demand response is included. This directly relates to the opportunity to avoid OCT and GCT power generation, already mentioned when discussing generation output levels. Not only up-, but also downward price spikes are reduced. The amount of wind power curtailment is reduced. Those moments occur during hours with high wind power injections, and especially in the scenario with extra injections (underestimation).

### 5.3.3 Operational costs

Operational costs and environmental benefits are summarized in Table 3 and Table 4. The results account for the three scenarios with their respective 33.3% probability and can be interpreted as expected costs and environmental benefits. We assume one scenario with a correct wind power forecast and two scenarios with each a forecast error respectively included as an over- and underestimation. Without price-based demand response, an operational cost increase can be concluded when forecast errors increase. A higher deviation from the correct forecast gives higher generation as well as start-up costs.

Table 4 lists the results for the unit commitment model with price-based demand response. When consumers are able to adjust their initial levels of demand, different forecast error scenarios can be better dealt with. A price-responsive demand-side helps avoiding increasing operational costs due forecast errors. This conclusion is based on avoided GCT and OCT generation output and less power plants being partly loaded (Figure 8). Consequently, expected operational costs are reduced by 10%, given a 10% forecast error, up to 15%, for a 25% forecast error, assuming -0.15 own-price elasticity. Consequently, demand-side participation could be seen as an alternative to improving forecasting tools in order to reduce the cost of forecasting errors. In reality, demand-side participation and forecasting tool improvements must be simultaneously applied.

*Table 3: Operational costs and environmental benefits with wind power uncertainty: without price-based demand response*

| Forecast error | Total costs [€] | Generation costs [€] | Start-up costs [€] | Emissions [ton] | Curtailment [MW] |
|---|---|---|---|---|---|
| 10% | 1.912.952 | 1.636.777 | 8.219 | 22.540 | 1.419 |
| 15% | 1.946.277 | 1.660.893 | 8.364 | 22.555 | 1.716 |
| 20% | 1.988.563 | 1.684.882 | 8.803 | 22.559 | 2.310 |
| 25% | 2.037.096 | 1.721.153 | 8.559 | 22.634 | 2.701 |

*Table 4: Operational costs and environmental benefits with wind power uncertainty: with -0.15 own-price elastic demand response*

| Forecast error | Total costs [€] | Generation costs [€] | Start-up costs [€] | Emissions [ton] | Curtailment [MW] |
|---|---|---|---|---|---|
| 10% | 1.736.368 | 1.511.963 | 6.900 | 21.697 | 18 |
| 15% | 1.755.450 | 1.524.797 | 6.900 | 21.677 | 233 |
| 20% | 1.733.816 | 1.501.356 | 6.900 | 21.253 | 434 |
| 25% | 1.748.977 | 1.509.517 | 6.900 | 21.184 | 691 |

#### 5.3.4 Environmental benefits

When consumers adjust their demand levels in response to electricity prices, carbon emissions can be reduced by 5%. Furthermore, increasing forecast errors result in higher levels of wind power curtailment. When demand levels cannot be adjusted in response to prices, an oversupply of wind power must be increasingly curtailed with increasing forecast error. However, a flexible demand-side significantly impacts the amount of wind power curtailment. As suggested by the results in Table 4, smaller forecast errors can easily be absorbed by adjusting initial demand. A total level of curtailment of 1.419 MW in case of 10% forecast error can be reduced to 18 MW thanks to price-based demand response. When the total level of curtailment is raised up to 2.701 MW, assuming a 25% forecast error, a flexible demand-side can reduce curtailment down to 691 MW.

## 6. CONCLUSIONS

Unit commitment models optimize short-term operation of available generation units, accounting for technical constraints. Typically, demand levels are assumed to be fixed and system flexibility fully originates from generation. However, the smart meter roll-out, allowing real-time billing, creates flexibility at the demand-side of the electric power system. This yields value with respect to generation cost reductions and wind power integration, which is quantified in this paper.

Price-based demand response is included in a basic unit commitment model. Consumers are assumed to adjust initial demand levels in response to price changes. In order to include the benefits consumers receive from electricity consumption, fixed demand levels are replaced by hourly elastic demand functions. A more flexible demand-side is included by increasing the absolute value of the own-price elasticity.

Increasing consumer's responsiveness to price deviations on the one hand reduces peak demand levels, avoiding expensive peak and high peak load power generation. On the other hand, demand valleys with low electricity demand or excess wind power generation can be filled, increasing the output of less expensive power generation. Consequently, the capacity factor of base load generation increases, whereas this factor decreases in case of peak load generation. In addition to those cost reductions, price volatility is lower and the integration of non-dispatchable wind power generation is improved.

Finally, a flexible demand-side proofs to be efficient in dealing with the unpredictability of real-time wind power injections. A stochastic unit commitment model indicates that the issue of wind power forecast errors can partly be solved at by demand-side flexibility. As the instantaneous system power balance is no longer only achieved by supply-side measures, a large amount of wind power can be integrated into the system without a significant operational cost increase.

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