Project work

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Value of Price Dependent Bidding for Thermal Power Producers

Teaching supervisor: Stein-Erik Fleten

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Trondheim, December 2013

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Abstract

The steady increase in the short-term trading of electricity through power markets has made the investigation of appropriate bidding strategies relevant. The object of this report is to compare price-dependent and price-independent bidding strategies. This is done through three case studies where the two bidding strategies are evaluated under different conditions based on German-Austrian price data from EPEX SPOT. The results indicate that in some circumstances where the power producers have sufficient generation capacity to avoid infeasible solutions, power producers are able to utilize the value of flexible bidding. For power producers without this flexibility, price-independent bids are likely to give better results.

Preface

This report is a project thesis written within the field of Applied Economics and Operations Research at the Department of Industrial Economics and Technology Management, University of Science and Technology (NTNU). The authors would like to thank Stein-Erik Fleten and Gro Klæboe for their guidance and insight in the problem at hand, Christian Skar for help with model implementation and FICO for access to their Xpess solver.

Trondheim 17 December 2013

Erik B. Rudlang Carl Fredrik Tjeransen

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Chapter 1

Nomenclature

Indexes

s	index of price scenarios
t	index of time steps
i	index of price points
j	index of thermal units
l	index of unit start up types

Sets

S	set of scenarios
T	set of time steps for the planning period
T^B	set of time steps for the planning period, subset of T
T^-	planning horizon extended to the past
I	set of price points
J	set of thermal units
L	set of unit start up types $L = \{h, w, c\}$ where h=hot, w=warm, c=cold

Parameters

ρ_t^s	$t \in T,\ s \in S$	realized price at time step t in scenario s
p_i	$i \in I$	bidding price at price point i
π^s	$s \in S$	probability of scenario s
c_j	$j \in J$	marginal cost of in unit j
C_j^l	$j \in J,\ l \in L$	start up cost of start up type l in unit j
C_j	$j \in J$	commitment cost unit j per hour
RL_j	$j \in J$	ramping limit in unit j
UT_j	$j \in J$	minimum up time in unit j
DT_j	$j \in J$	minimum down time in unit j
$\overline{P_j}$	$j \in J$	maximum output of unit j
$\underline{P_j}$	$j \in J$	minimum output of unit j
$\overline{T_j^l}$	$j \in J,\ l \in L$	number of time steps specifying start up type l in unit j
T_{max}		number of time steps in the planning horizon T
R		penalty for using the balance market

Variables

x_{it}	$i \in I,\ t \in T^B$	volume bid at price point i in time step t
y_t^s	$t \in T,\ s \in S$	volume committed at time step t in scenario s
z_{jt}^s	$j \in J,\ t \in T,\ s \in S$	volume produced in unit j at time step t in scenario s
${}^+q_t^s$	$t \in T,\ s \in S$	volume sold in the balancing market at time step t in scenario s
${}^-q_t^s$	$t \in T,\ s \in S$	volume bought in the balancing market at time step t in scenario s
u_{jt}^s	$j \in J,\ t \in T^-,\ s \in S$	binary variable that is equal to 1 if unit j runs at time step t in scenario s
v_{jt}^s	$j \in J,\ t \in T^-,\ s \in S$	binary variable that is equal to 1 if unit j shuts down at time step t in scenario s
w_{jt}^s	$j \in J,\ t \in T^-,\ s \in S$	binary variable that is equal to 1 if unit j is started in time step t in scenario s
w_{jt}^{ls}	$l \in L,\ j \in J,\ t \in T^-,\ s \in S$	binary variable that is equal to 1 if a type l start up is initiated in time step t in unit j

$\delta_t^s \quad t \in T,\ s \in S$	binary variable that is equal to 1 if producer uses the balancing market
$C^{prod}(z_{jt}^s, u_{jt}^s, w_{jt}^{ls})$	aggregated variable costs
$C^{balance}({}^+q_t^s, {}^-q_t^s)$	cost of using the balance market

Chapter 2

Introduction

Power producers that wish to take part in an electricity spot-market must develop appropriate bidding strategies. The problem of finding optimal bidding decisions relies on the success in different areas such as market modeling, production planning and bid generation. For thermal power producers who are restricted by temporal constraints in the power generation the bidding process is even more complex. Price-independent bids are promoted as a way to reduce the risk of unpredicted market events that might leave the power producer unable to fulfill the market obligation [17]. However, these bids are inflexible and incapable of responding to price signals from the market. Price-dependent bidding, on the other hand, has the potential to better react to unforeseen market events, but might leave the power producer unable to fulfill the market commitment through self-scheduling.

This report will try to analyze the differences between price-dependent and price-independent bidding through three different case studies based on the German-Austrian spot-market. Two stochastic optimization models are presented in chapter 3. These modelse can be used to generate price-dependent and price-independet bids. In chapter 4 a forecasting and scenario generation method is introduced. The value of the two bidding strategies is assessed through three case studies in chapter 5. A discussion on the findings is found in chapter 6 followed by a conclusion in chapter 7.

2.1 Metric for value of price-dependent bidding

The authors have no knowledge of previous research on the difference in the value for price-dependent and price-independent bidding in the spot market for thermal power producers. This report proposes a new metric to structure the further study of this problem.

Taking ideas from the concept of the Value of the Stochastic Solution (VSS) [1] a similar Value of Price-Dependent Bidding (VPDB) is proposed to reflect the value of including the flexibility of price-dependent bidding into the bidding model. VPDB is the optimal objective value of the price-dependent bidding problem subtracting the optimal objective value of the price-independent bidding problem. To be able to evaluate the value of price-dependent bidding between different models, a relative value of price-dependent bidding is defined as the VPDB divided by the optimal objective value of price-independent bidding problem.

Table 2.1: Definition of Value of Price-Dependent Bidding (VPDB) and Relative Value of Price-Dependent Bidding RVPDB

$$VPDB = f(x^*_{PD}) - f(x^*_{PI}) \tag{2.1}$$

$$RVPDB = \frac{VPDB}{f(x^*_{PI})} 100\% \tag{2.2}$$

2.2 Literature

The purpose of this report is the study of two different bidding strategies that has been discussed in the literature, but not compared. A short presentation of the literature in this field follows:

The deregulation of the power market has led to a new reality for power producers with competition and market pressure. Before the deregulation there was a central dispatch that solved a Security Constrained Unit Commitment (SCUC) to reduce the socio-economic cost. After deregulation each producer has to solve its own Price-Based Unit Commitment Problem (PBUC). The similarities and differences between the PBUC and SCUC are discussed by Yamin in [31].

The PBUC can take multiple forms depending on the market structure that the power producer faces. In [27, 23, 28] the power producer is assumed to be a price-taker and has no influence over the market clearing price. An appropriate forecasting tool is used to estimate the hourly electricity prices for the next day, and the PBUC is solved based on the price expectation. The PBUC has also been used where the power producer holds market power. One example is [6] which presents a formulation where the power producers can influence the market price through a quota scheme.

The thermal unit commitment problem is a mixed integer problem (MIP) that has been an active research topic for decades. Several solution techniques have been proposed such as heuristics, dynamic programming, mixed-integer linear programming, Lagrangean relaxation, simulated annealing and evolution-inspired approaches. A literature survey in the field of the unit commitment problem is done in [20].

The PBUC is used to find the optimal unit commitment given a price signal, and it is an important component in models that find bidding strategies for power producers. In the papers [4, 22, 17] bids are developed using the solution of the PBUC. In [4] bidding curves are derived from the statistical properties of the price estimator. Bids are specified such that the optimal quantity lies within a confidence interval of the price estimator. In [17] the deterministic problem is solved a number of times for different offsets in price to obtain bidding curves for a range of prices. A multistage scenario tree is developed in [22] and the solution to the deterministic equivalent problem is used as bidding curves.

The operation of an electricity market requires power producers to submit bids before actual production to settle market clearing prices and quantities. A more detailed description of the role of power exchanges can be found in [25, 29]. This procedure can be modeled as a two-stage problem where optimal bids are determined in the first stage on the basis of unit commitment in the second stage. The PBUC can thus be extended to a stochastic model where the first stage decision is done under uncertainty [28].

In [19] the spot market is explicitly modeled as a two-stage stochastic problem where own bids are decided in the first stage, and the realized spot price is a function of own and realized bids of other power producers in the second stage. This approach requires knowledge of competitors bidding functions and cost structure and can only be used where this information is available. A two-stage formulation that assumes the power producer to be a price-taker is found in [10, 9]. Second stage production decisions are related to first stage bidding decisions through a coupling constraint. By fixing a set of price points, [9] is able to obtain a linear problem that can be solved with standard MIP solvers.

There are a number of physical and economical limitations on thermal power plants. The level of detail which these constraints have been modeled varies among different papers. The general problem formulation can be found in [20]. Paper [27] extends this formulation to include different operating states of the generators and start up types.

Chapter 3

Optimization model

3.1 The bidding problem

Power producers participating in an electricity spot-market may submit different types of bids. Two of these are: Price-independent and price-dependent bids. Price-independent bids consists of one volume for each hour and will be accepted regardless of the price in the market. Price-dependent bids consist of a set of price-volume pairs which makes up a bidding curve for each hour. The bidders are allowed to submit bids up until 12 hours before operation day. After the auction deadline, the bids submitted both by power producers and consumers are aggregated and the system price and commitment in each time period is reported to the participants.

To participate in these markets, thermal power producers need to schedule production and submit bids ahead of time. The resulting problem is therefore a two stage stochastic problem. The value of including the stochasticity of the problem into the model when solving stochastic problems is reported in the literature [13, 24]. These programs produce robust solutions that have the potential of higher returns when recourse decisions are present.

In the following section two models are presented. In section 3.2 the Profit-Based Unit Commitment Problem is formulated as a two-stage price-dependent bidding problem and in section 3.3 the Profit-Based Unit Commitment Problem is formulated as a two-stage price-independent bidding problem.

3.2 Price-dependent bidding problem

The objective function (3.1) maximizes the power producers profit, where profits equal the committed volume of electricity at the realized electricity price minus the corresponding operating costs and the cost for use of the balancing market.

$$\max = \sum_{s=1}^{S} \pi^s \left\{ \sum_{t=1}^{T} \rho_t^s y_t^s - C^{prod}(z_{jt}^s, u_{jt}^s, w_{jt}^{ls}) - C^{balance}({}^+q_t^s, {}^-q_t^s) \right\} \quad (3.1)$$

3.2.1 Operating cost

The operating costs (3.2) consist of the marginal production cost, the commitment cost, and the start-up cost for the different start-up types. See section 3.2.5 for details on different start-up types.

$$C^{prod}(z_{jt}^s, u_{jt}^s, w_{jt}^{ls}) = \sum_{t=1}^{T}\sum_{j=1}^{J} c_j z_{jt}^s + \sum_{t=1}^{T}\sum_{j=1}^{J} C_j u_{jt}^s + \sum_{l=1}^{L}\sum_{t=1}^{T}\sum_{j=1}^{J} C_j^l w_{jt}^{ls} \quad s \in S \quad (3.2)$$

3.2.2 Bidding curves

The bidding curves are piece-wise linear convex functions where price-volume pairs determines each line piece. The problem of finding both prices and quantities results in a non-linear problem. To avoid non-linearities the same approach as in [10] has been used where price points (p_i) are fixed and the problem is solved for quantity variables (x_{it}). The interpolation between the price-volume points and the realized price in each scenario (ρ_t^s) gives the producers committed volume (y_t^s) (3.3).

$$y_t^s = \begin{cases} \frac{\rho_t^s - p_1}{p_2 - p_1} x_{2t} + \frac{p_2 - \rho_t^s}{p_2 - p_1} x_{1t} & \text{if } p_1 \leq \rho_t^s < p_2 \\ \vdots \\ \frac{\rho_t^s - p_{i-1}}{p_i - p_{i-1}} x_{it} + \frac{p_i - \rho_t^s}{p_i - p_{i-1}} x_{i-1t} & \text{if } p_{i-1} \leq \rho_t^s < p_i \\ \vdots \\ \frac{\rho_t^s - p_{I-1}}{p_I - p_{I-1}} x_{It} + \frac{p_I - \rho_t^s}{p_I - p_{I-1}} x_{I-1t} & \text{if } p_{I-1} \leq \rho_t^s < p_I \end{cases} \quad (3.3)$$

As required by the EPEX SPOT Operational Rules, Article 1.5.1 [26] the bid has to be monotonous. This implies that with increasing prices the volume has to equal or exceed the previous bid volume (3.4).

$$x_{it} \leq x_{i+1,t} \qquad i \in I, t \in T \quad (3.4)$$

By fixing the set of price points as in [10], bidding decisions might have to be made for prices that are not within the set of realized prices (ρ_t^s) for the respective time step. To reduce the risk of infeasible commitments quantity variables for price points outside the range of realized prices for each hour is set equal the quantities assigned to the last price point with information (3.5) (3.6).

$$x_{i+1,t} = x_{it} \qquad |max(\rho_t^s) < p_i \qquad i \in I, t \in T \tag{3.5}$$
$$x_{i,t} = x_{i+1,t} \qquad |min(\rho_t^s) > p_i \qquad i \in I, t \in T \tag{3.6}$$

3.2.3 Balancing market

The model includes the use of a balancing market to satisfy second stage restrictions. The balancing market is modeled as a penalty function (3.9) and upper limits on the sales and purchases in the balancing market (3.7) (3.8). To promote feasible first stage decisions, both the sale and purchase in the balancing market is related to a penalty. The penalty is a fixed deviation from the electricity price (R).

$$^{+}q_t^s \leq \delta_t^s \sum_{j \in J} \overline{P_j} \qquad s \in S, t \in T \tag{3.7}$$
$$^{-}q_t^s \leq (1 - \delta_t^s) \sum_{j \in J} \overline{P_j} \qquad s \in S, t \in T \tag{3.8}$$
$$C^{balance}(^{+}q_t^s, ^{-}q_t^s) = (\rho_t^s + R)^{-}q_t^s - (\rho_t^s - R)^{+}q_t^s \qquad s \in S, t \in T \tag{3.9}$$

3.2.4 Thermal constraints

Thermal power plants have technical constraints that couples the production in different time periods together. The formulation in [27] is used to describe these technical constraints. The maximum and minimum output of power for each unit is restricted in (3.10) and (3.11).

$$z_{jt}^s \leq \overline{P_j} u_{jt}^s \qquad s \in S, t \in T, j \in J \tag{3.10}$$

$$z_{jt}^s \geq \underline{P_j} u_{jt}^s \qquad s \in S, t \in T, j \in J \tag{3.11}$$

The maximum change in production in one unit from one time step to the next is limited by the ramp-up (3.12) and ramp-down (3.13) restrictions.

$$z_{jt}^s \leq z_{jt-1}^s + RL_j \qquad s \in S, t \in T, j \in J \tag{3.12}$$

$$z_{jt}^s \geq z_{jt-1}^s - RL_j \qquad s \in S, t \in T, j \in J \tag{3.13}$$

The limitation on minimum up and down time is enforced by (3.14) and (3.15).

$$\sum_{\tau=t-UT_j+1}^{t} w_{j\tau}^s \leq u_{jt}^s \qquad s \in S, t \in T, j \in J, \text{where } \tau \in T^- \tag{3.14}$$

$$\sum_{\tau=t-DT_j+1}^{t} v_{j\tau}^s \leq 1 - u_{jt}^s \qquad s \in S, t \in T, j \in J, \text{where } \tau \in T^- \tag{3.15}$$

3.2.5 Logical constraints

Equation (3.16) ensures that production, commitment and use of the balancing market are in balance.

$$\sum_{j\in J} z_{jt}^s = y_s^t - q_t^{+s} + q_t^{-s} \qquad s \in S, t \in T \tag{3.16}$$

In (3.17) the start variable (w_{jt}^s) will be forced to 1 if a unit runs in one time step ($u_{jt}^s = 1$) and is off in the previous time step ($u_{jt}^s = 0$). The stop variable (v_{jt}^s) will in the same manner be forced to 1 if the opposite is true. If there is no change in the unit commitment the start and stop variables will not be affected. Equation (3.18) specifies that a unit cannot start and stop in the same time period.

$$w_{jt}^s - v_{jt}^s = u_{jt}^s - u_{jt-1}^s \qquad s \in S, t \in T, j \in J \tag{3.17}$$

$$w_{jt}^s + v_{jt}^s \leq 1 \qquad s \in S, t \in T, j \in J \tag{3.18}$$

The cost of a start-up increases with the time the plant has been shut down. This is modeled with different start-up types: hot, warm and cold. To assign the correct start-up type to the start-up variable, a time interval is specified that determines each start-up type (3.19) [27]. The start-up variable is further limited in (3.20) by the fact that there can only be one start-up type in any time period on any generator.

$$w_{jt}^{ls} \leq \sum_{\tau=t-\overline{T}_j^l+1}^{t-\underline{T}_j^l} v_{jt}^s \qquad s \in S, t \in T, j \in J, l \in L, \text{where } \tau \in T^- \tag{3.19}$$

$$w_{jt}^s = \sum_{l\in L} w_{jt}^{ls} \qquad s \in S, t \in T, j \in J \tag{3.20}$$

3.2.6 Initialization constraints

The state of the system at the start of the planning period influences the bidding problem. Instead of a predefined initial state the starting conditions are model by a wrap around formulation similar to what is done in [21]. For the production (z^s_{jt}) and commitment (u^s_{jt}) variables this is done by connecting the initial period ($t = 0$) to the last period ($t = T_{max}$) (3.21) ,(3.22).

$$z^s_{j,0} = z^s_{j,T_{max}} \qquad s \in S, j \in J \tag{3.21}$$

$$u^s_{j,0} = u^s_{j,T_{max}} \qquad s \in S, j \in J \tag{3.22}$$

For the start (v^s_{jt}) and stop variables (w^s_{jt}) a larger time frame is needed to determine the start-up type and the minimum up-time and down-time (3.14), (3.15). This if formulated in equations (3.23), (3.24).

$$v^s_{j,t-T_{max}} = v^s_{j,t} \qquad s \in S, t \in T, j \in J \tag{3.23}$$

$$w^s_{j,t-T_{max}} = w^s_{j,t} \qquad s \in S, t \in T, j \in J \tag{3.24}$$

3.3 Price-independent bidding problem

The price-independent bidding problem is a stochastic two-stage problem similar to the price-dependent bidding problem. In the price-dependent model price points were used to give volumes at different prices. In the formulation of the price-independent model, price points are not needed since the bid only consists of one volume per hour. The whole set I can therefore be left out of the model. The bid variable will thus only be dependent on time step t. The omission of price points leaves restrictions (3.3), (3.4), (3.5) and (3.6) redundant. However, to keep the coupling between the volume bid (x_t) for each hour and the sales variable (y^s_t), equation (3.25) is needed.

$$x_t = y^s_t \qquad t \in T, s \in S \tag{3.25}$$

Chapter 4

Scenario generation

Box and Jenkins introduced the application of ARIMA models to the study of time series [2] which have been extensively used to model electricity price behavior [5, 9]. In this chapter the process of finding an ARMA model to be used for electricity price forecasting is presented.

4.1 ARMA time series analysis

The ARMA process consists of both autoregressive (AR) and moving average (MA) components and is defined as:

$$y_t = c + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t \tag{4.1}$$

The ϕ_i correspond to the parameters for the AR terms, where p is the order of the AR part. The θ_i are the parameters corresponding to the MA terms, where q is the order of the MA part. c is a constant and (ε_t) are the error terms of the stochastic process. The assumptions of the ARMA process on the error terms are; zero mean (4.2), constant variance (4.3), and zero correlation (4.4).

$$E(\varepsilon_t) = 0 \tag{4.2}$$

$$E(\varepsilon^2) = \sigma^2 \tag{4.3}$$

$$E(\varepsilon_t \varepsilon_s) = 0, s \neq t \tag{4.4}$$

A methodology for determining an appropriate ARMA model to use for price forecasting is proposed based on Box and Jenkins methodology. The methodology consists of the five steps outlined in Table 4.1.

Table 4.1: The Box and Jenkins methodology

1. A class of models is formulated
2. A subset of models is identified
3. Parameter estimation
4. Statistical hypothesis testing to validate the model. If the model is validated go to Step 5, else proceed to Step 2.
5. Forecasting

4.1.1 Class of models

This step concerns the identification of a general class of models based on the inspection of the main characteristics of the hourly prices. The hourly electricity prices in the German-Austrian spot market presents high frequency, non-constant mean and variance, and multiple seasonality (daily and weekly). The proposed general ARMA formulation is the following:

$$\phi(B)p_t = \theta(B)\varepsilon_t \tag{4.5}$$

B is the backshift operator.

The ARMA formulation (4.5) is sufficiently general to include the main features of the price data.

4.1.2 Subset of ARMA models

In order to make the underlying process stationary a log transformation of the data was performed. A trial model (4.6) was formed based both on data analysis of the auto correlation and partial autocorrelation plots of the price data.

$$\begin{aligned}(1 - \phi_1 B^1 - \phi_2 B^2 - &\phi_3 B^3 - \phi_4 B^4 - \phi_5 B^5 - \phi_{24} B^{24} - \phi_{168} B^{168}) y_t \\ &= (1 - \theta_{24} B^{24} - \theta_{168} B^{168}) \varepsilon_t \end{aligned} \tag{4.6}$$

4.1.3 Parameter estimation

Good estimators of the parameters in the model can be obtained by assuming the data is of a stationary time series. The parameters are estimated by using statistical software that performs a maximum likelihood estimation of the parameters. Due to limitations in the available software, it was not possible to include seasonality beyond the 24 hour period. An algorithm that extends the functionality to multiple seasons is proposed in [7], but implementing and testing this algorithm was outside the scope of this report.

4.1.4 Model evaluation

In this step, statistical hypothesis testing was performed to validate the model assumptions. This included tests on the significance of the parameters of the model, the assumptions in equation (4.4) was tested through the Ljung-Box statistic, and analysis of the autocorrelation and partial autocorrelation functions for the relevant lags. A Breusch-Pagan test was performed to test the assumption in equation (4.3) of constant variance in the residuals.

The assumption that the errors form a white noise process that is normally distributed is not supported in this analysis. As with [3] the results support the rejection of electricity price changes as normally distributed. This has implications for the forecasting procedure discussed in the next section.

Although autoregressive lags of up to four time steps were identified as statistically significant in the model evaluations, an Akaike Information Criterion test showed that adding lags beyond the two first terms did not significantly improve the model. This was also supported through only incremental improvements in the R^2 value as more lags were added.

4.1.5 Forecasting

As a result of the previous steps a final model (4.7) for the German-Austrian electricity market was found.

$$(1 - \phi_1 B^1 - \phi_2 B^2 - \phi_{24} B^{24}) \log(y_t - \alpha) = (1 - \theta_{24} B^{24})\varepsilon_t \tag{4.7}$$

The model is a simple model compared to [5, 11], but sufficient to be able to perform initial tests on the value of price dependent bidding. The final model can be used to forecast prices into the future. The estimated parameters of this model can be seen in Table 4.2.

Table 4.2: Estimated parameters for the ARMA price model

	$\phi_1 B^1$	$\phi_2 B^2$	$\phi_{24} B^{24}$	$\theta_{24} B^{24}$	α
	1,0454	-0,1391	0,9927	-0,9042	5,2312
s.e.	0,0122	0,0122	0,0017	0,0072	0,0344

4.2 Numerical results

In the empirical analysis the proposed ARMA model was applied to the German-Austrian electricity data. The data set consisted of price data from 1 January 2013 to 1 October 2013. To evaluate the performance of the suggested price model an in-sample analysis was conducted. As in [5, 11] an in-sample analysis based on the last week of every month in the 8 month data set was performed. The mean week error (MWE) is compared to the standard deviation of the error terms of the forecasting model $\hat{s}_R$. The $\hat{s}_R$ is used as an estimate of the true variance of the error terms (σ^2) and describes the variance of what is still unexplaiend after fitting the model.

Table 4.3: Mean weakly error in the forecast for last seven days in the month.

Month	MWE (%)	$\hat{s}_R$
February	19.3 %	7.5099
March	19.5 %	8.7618
April	21.4 %	8.1139
May	25.2 %	6.3729
June	30.9 %	6.2934
July	22.4 %	5.8796
August	23.9 %	6.5052
September	-887.1 %	9.8229

As with [5, 11], it is found that the proposed ARMA model performs poorly under high volatility , and inable to give predictions in the week of extreme volatility in September (Figures 4.2, 4.2 and Table 4.4]. Combining the forecasting tool with our scenario generation approach it was possible to obtain simulations of the German-Austrian market.

Table 4.4: Mean daily error in the forecast for the last last seven days of February and September 2013

Day	1	2	3	4	5	6	7
February	8.02 %	19.3 %	28.5 %	19.5 %	22.6 %	25.1 %	12.1 %
September	32.5 %	28.7 %	23.4 %	19.7 %	24.5 %	6358.0 %	18.8 %

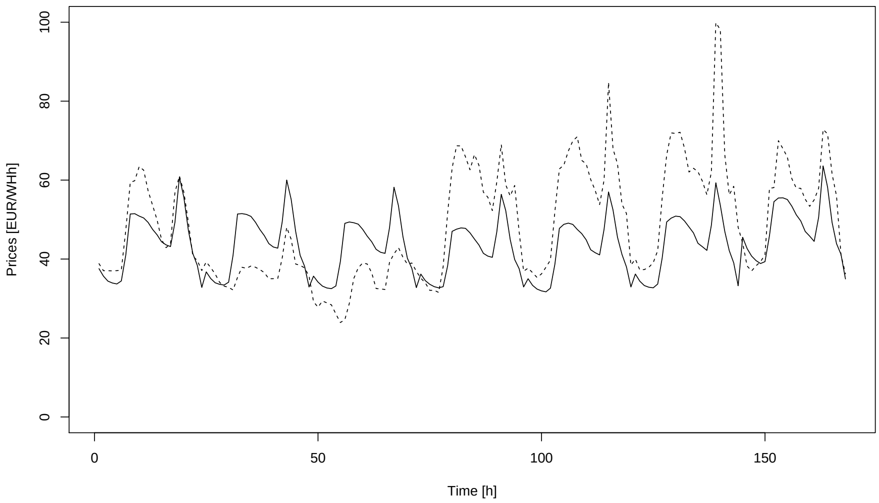

Figure 4.1: Forecasting error for the last seven days of February 2013. Solid line is forecasted value, dotted line is the real value

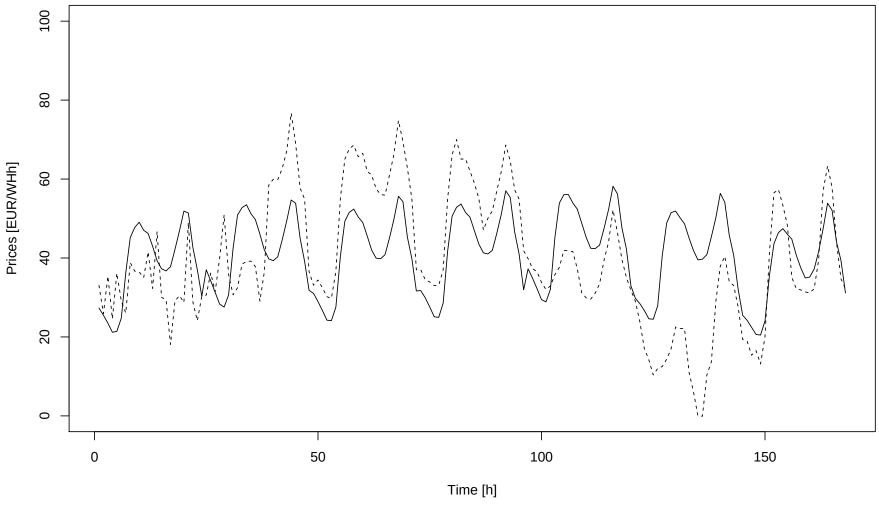

Figure 4.2: Forecasting error for the last seven days of September 2013. Solid line is forecasted value, dotted line is the real value

The forecasted prices for Wednesday 2 October 2013 and next six days were measured against the realized prices of the same week to analyze the out-of sample performance (Figure 4.2 and Table 4.5].

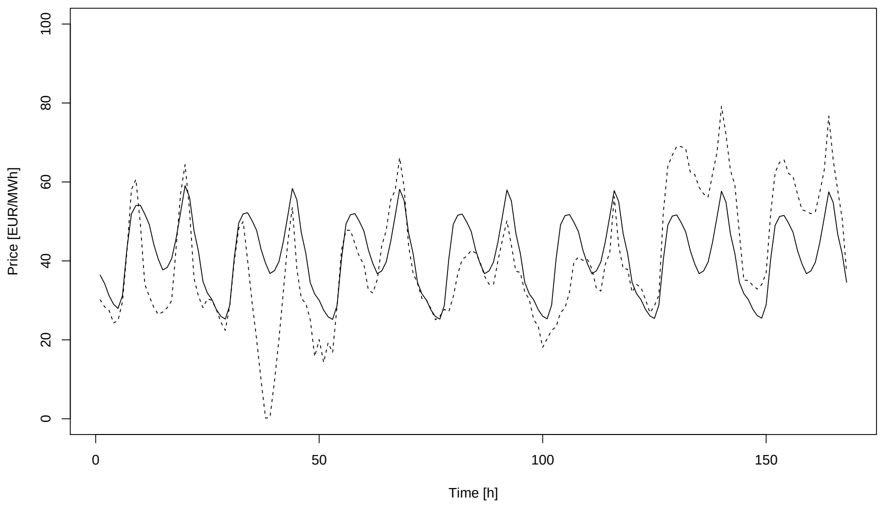

Figure 4.3: Forecasting error for the 2-8 October 2013
Solid line is forecasted value, dotted line is the real value

Table 4.5: Mean daily error for 2-8 October 2013

Day	1	2	3	4	5	6	7
Mean daily error	24.1 %	1527.9 %	29.5 %	20.7 %	32.8 %	20.3 %	16.7 %

4.2.1 Exogenous variables

Additional exogenous variables could have improved the modeling effort. Especially the time-dependent influx of solar power in the day-time could have explained more of the variation in the price data. Since this correlation is largely time-dependent, some of this variation is compensated for by a sampling approach discussed in the next section. The significance of different weekdays, more specifically Saturday, Sunday and Monday could have been included.

4.3 Scenario generation

A stochastic optimization model needs a finite and discrete representation of the stochastic variables to be used as input into the model. When discrete distributions of the stochastic variables are obtained, these needs to be linked appropriately to reflect the decision stages and periods in the planning horizon. The resulting representation is a scenario tree that defines the information structure of the problem. There have been different methods proposed to derive this discrete distribution, and the construction of a scenario tree. There is a short overview in [15] which also presents two important properties that a scenario generating method should satisfy. In the next sections a scenario generation approach is presented and the stability of the approach is evaluated

4.3.1 Method

The information structure of the bidding problem is illustrated in Figure 4.4. Initial bidding decisions are made in the first step, and subsequent recourse production decisions are made in the second step based on the realization of the market prices in the day-ahead market. The modeling effort in chapter 4 resulted in an ARMA model that can be used for price forecasting. This stochastic process was used to forecast prices for the week starting 2nd of October 2013 in the German-Austrian electricity market. As the error terms of the ARMA model were not normally distributed, the simulations were based on the residuals from the price model. These residuals were grouped into independent samples for each hour and when predictions were made, random draws from these samples were performed.

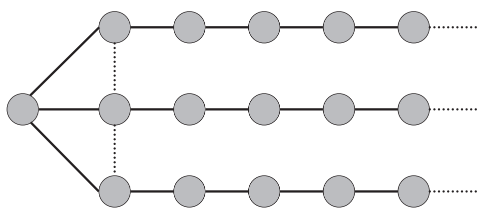

Figure 4.4: The information structure of the bidding problem

4.3.2 Scenario reduction and convergence

To be able to sufficiently describe the stochastic variables and at the same time obtain a workable set of scenarios, a large set of scenarios were generated and then reduced through a scenario reduction algorithm. 5000 scenarios were generated and the scenario reduction algorithm proposed in [12] (SCENRED 2.1) based on forward selection was used to reduce this set of scenarios. The algorithm is designed to reduce the set while minimizing the probability distance between the distributions. The relative probability distance increases as the set of 5000 scenarios is reduced to smaller sets of scenarios (Figure 4.5). An overview of scenario reduction and the forward selection algorithm is given in [8]. In the analysis of the reduced set of scenarios it was found that the algorithm modified the tails of the distribution by reducing the number of extreme values.

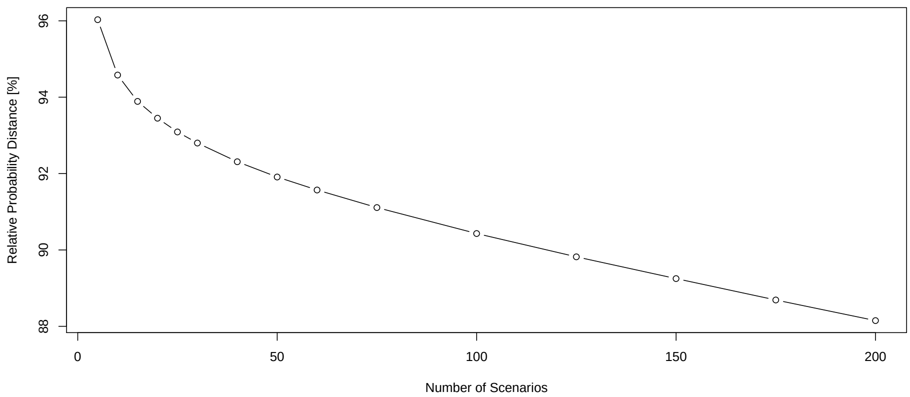

Figure 4.5: Relative probability distance in scenario reduction of 5000 scenarios

4.3.3 Stability

The stability of the scenario generation method is the ability of the method to produce scenario trees that give similar optimal solutions [15]. To be able to evaluate the stability of the proposed scenario generation method the convergence of the model to the scenarios was analyzed similar to [22]. Figure 4.6 shows the convergence of the scenario generation method.

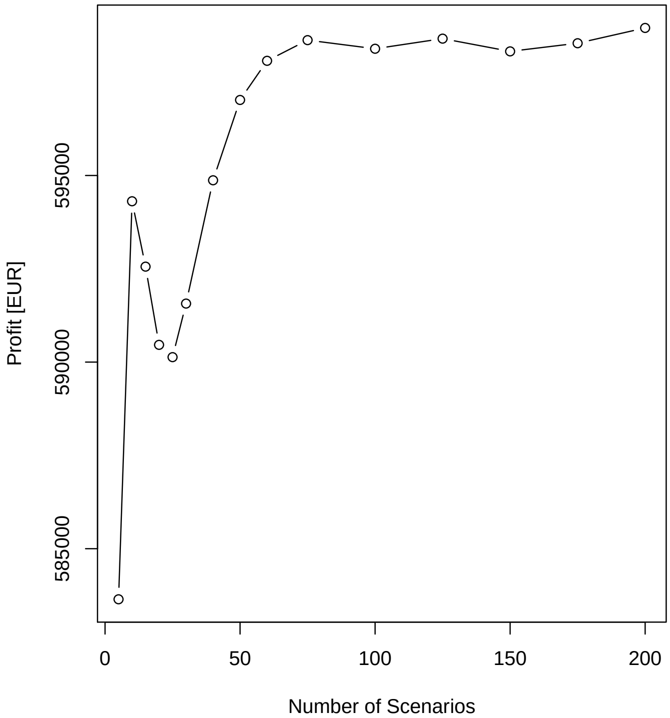

Figure 4.6: Stability of the price model with increasing number of scenarios

Chapter 5

Case study

The differences between price-dependent bidding and price-independent bidding is analyzed in three cases. The first case uses scenarios generated from the price- proposed in 4 as input into the optimization models. In the second case bids are generated using historical data from EPEX SPOT as input. To see the impact of higher average prices and more unites committed, the third case shifts the historical data up by 15 EUR/MWh. It has been the hypothesis of the authors that the value of price-dependent bidding should increase with increased flexibility as the price-dependent bids are flexible where the price-independent bids are not. In all three cases an out-of-sample analysis was performed to compare the two bidding strategies. In order to better evaluate the bidding curves in each case, the solution of the unit commitment problem is presented first. In this section general considerations are made regarding the solution of the unit commitment problem for each scenario.

Throughout the case study the planning horizon is set to one week (168 hours) and the bidding horizon is set to 24 hours. In all cases the bid is for Wednesday the 2 October 2013 (chapter 4). The optimization model described in chapter 3 requires predefined price points for the price-dependent model. These points were selected on the basis of the input scenarios using the same methodology as in [18]. The number of price points were selected to ensure stable results in all cases.

5.1 Portfolio of generators

In the case studies the analysis is based on a portfolio of generators with characteristics as in Table 1. These are the same generators used in the case study in [27]. They consist of two lignite-based units, two combined cycle gas turbines (CCGT) and one open cycle gas turbine (OCGT). The different cost structure and technical constraints in the portfolio of generators makes a good starting point for the analysis of price-dependent and price-independent bidding.

Table 5.1: Generator costs [27]

Unit	Type	MargCost [EUR/MWh]	Run Time Cost[EUR/h]	Start Cost [EUR] Hot	Warm	Cold
1	lignite	29	1894	46600	64007	87217
2	lignite	31	1644	58165	79892	108862
3	CCGT	55	3367	16012	24832	42472
4	CCGT	55	3839	19766	30476	51896
5	OCGT	85	965	2568	2568	2568

Table 5.2: Generator thermal properties [27]

Unit	Power: [MW] Max	Min	MaxRamp [MW/min]	Time from stop to: Warm [h]	Cold [h]	Minimum time: [h] Start-Stop	Stop-Start
1	274	160	2	5	12	8	4
2	342	180	2	5	12	8	4
3	378	200	24	5	12	4	3
4	476	250	24	5	12	4	3
5	152	63	8	5	12	1	1

5.2 Case 1: Forecasted data

The optimization model is run using 75 scenarios generated from the price model. This number of scenarios was shown in chapter 3 to ensure stability and convergence of the optimization model. The variability of the prices can be seen to follow a band around the forecasted price. This is similar to [22]. The sampling approach discussed in chapter 4 resulted in a number of time steps where price changes included extreme values, this can be seen in Figure 5.1.

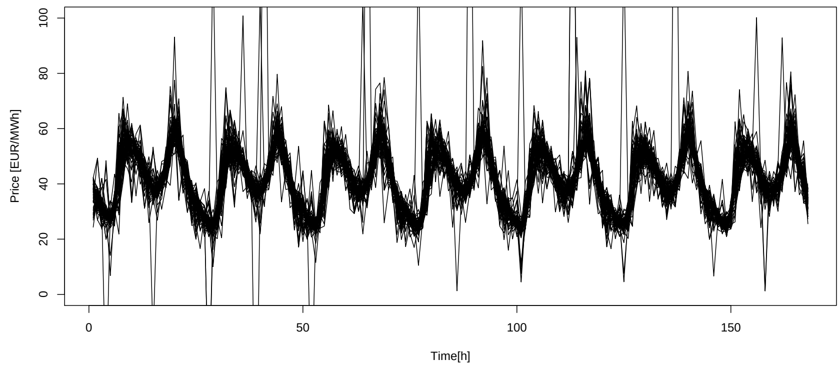

Figure 5.1: 75 scenarios generated from the price model used as input in the case 1

5.2.1 Unit commitment problem

The low price level in the German-Austrian market leaves the higher cost generators, unit 3-5, inactive as the price level cannot justify the operation of these generators. Thus the unit commitment problem reduces to the commitment problem of two generators, unit 1 and unit 2. In the solution both units are committed throughout the whole bidding period, for every scenario in both the price-dependent model and the price-independent model. In one scenario the price-dependent model is able to utilize the flexibility in unit 5 to exploit a price peak as illustrated in Figure 5.2.

5.2.2 Bidding strategies

The bidding curves from the price-dependent model (Figure5.4) reflects the low variation in the prices from the price model. In a number of time steps only a single bid is made, and it is only for time steps with extreme values that bidding decisions are made for a larger variation of prices. The expectation of low prices in the early hours of the 2nd of October results in the minimum capacity bid for unit 1 and unit 2 in the price-independent model (Figure 5.3).

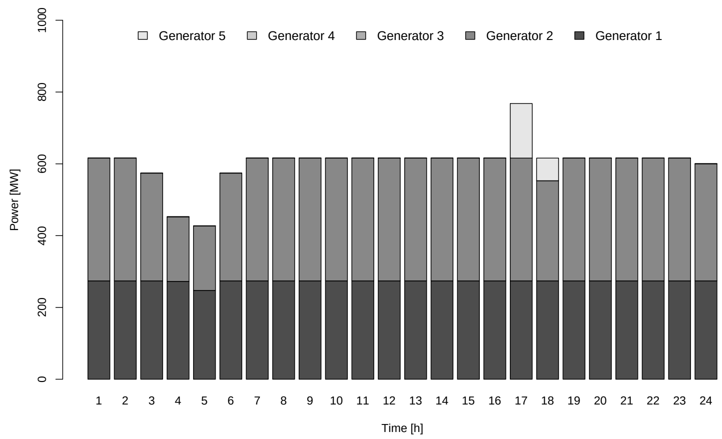

Figure 5.2: Example of production dispatch in the price-dependent model for one specific scenario where a price peak is exploited

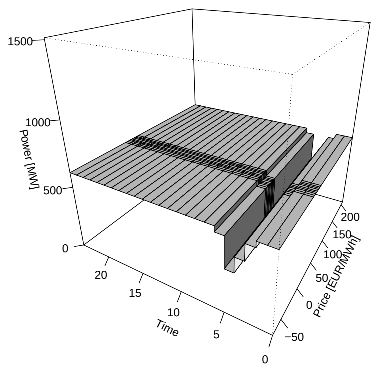

Figure 5.3: Bidding curves from the price-independent model in case 1

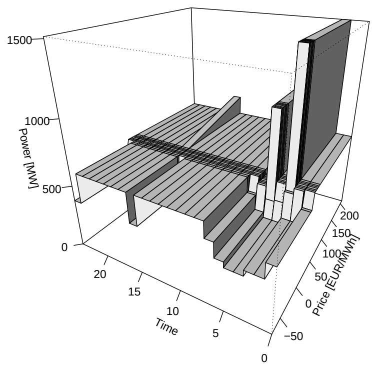

Figure 5.4: Bidding curves from the price-dependent model in case 1

5.2.3 Value of price-dependent bidding

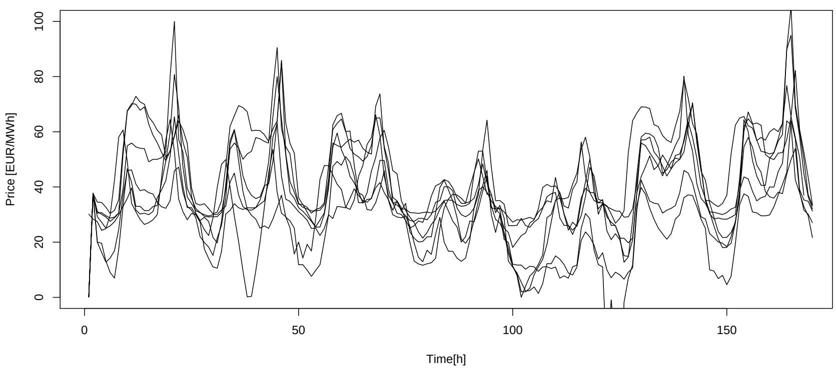

Figure 5.5: 7 consecutive weeks of price data starting from 2$^{\text{nd}}$ of October 2013 used for out-of-sample analysis

The bidding curves generated from the two optimization models weere tested in an out-of-sample test. Seven consecutive weeks of data from EPEX SPOT starting October 2nd (Figure 5.5) were used as input. The test was performed by fixing the bidding decisions, and running the optimization models with the new scenario set. Table 5.3 and Table 5.4 shows the result from this analysis. The tables illustrate the value of price-dependent bidding where the price-dependent bids performs better than the price-independent bids for all scenarios.

Table 5.3: Profit, VPDB and RVPDB with seven out-of-sample scenarios for fixed bidding decisions from both optimization models, with penalty of 0.5 EUR/MWh for the use of the balancing market

Scenario	Price-dep. bidding	Price-indep. bidding	VPDB	RVPBD
1	27233,4	26746,3	487,1	1,82 %
2	250750	250650	100	0.04 %
3	214453	214283	170	0.08 %
4	-6627.24	-7131	503.76	7.06 %
5	-6727.06	-7131	403.94	5.66 %
6	-30379	-30871	492	1.59 %
7	173380	173284	96	0.06 %
Mean	88869.01	88547.2	321,83	2 %

Table 5.4: Profit, VPDB and RVPDB with seven out-of-sample scenarios for fixed bidding decisions from both optimization models, with penalty of 10 EUR/MWh for the use of the balancing market

Scenario	Price-dep. bidding	Price-indep. bidding	VPDB	RVPBD
1	24837	22418	2419	10.79 %
2	250485	250249	236	0.09 %
3	214411	214186	225	0.11 %
4	-26357.5	-34538.3	8180,8	23.69 %
5	47114,1	44579.1	2535	5.69 %
6	-33089,9	-41717.1	8627,2	20.68 %
7	173244	172962	282	0.16 %
Mean	92949.1	89734.1	3215	8.74 %

5.3 Case 2: Historical data

The low variation in prices from the price model resulted in bidding curves that did not accurately reflect the high volatility in the German-Austrian market. In this section, historical data is used to be able to generate bids that span a larger variation of prices. The new bids were generated using 38 weeks of price data from EPEX SPOT (Figure 5.6).

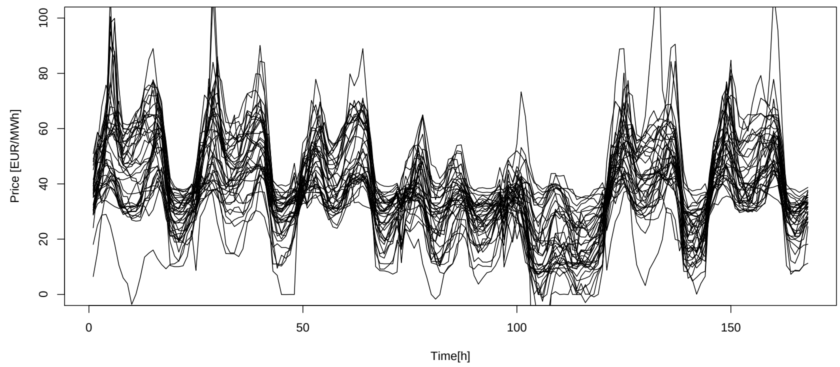

Figure 5.6: 38 weeks of historical data from EPEX SPOT for the German-Austrian market used as input in case 2 and in a shifted variant in case 3. The weeks start on a Wednesday.

5.3.1 Unit commitment problem

To find solutions in reasonable time, restrictions (3.19) and (3.20) in chapter 3 were relaxed to simplify the problem. The resulting problem corresponds to the general thermal unit commitment with one start-up type instead of the extended formulation proposed by [27]. The price level in the market is still too low to activate more of the portfolio. For both the price-dependent and the price-independent model only unit 1 and unit 2 is committed. However, the increased price variation leaves the price-dependent unit commitment significantly different from the price-independent as the price-dependent model can exploit the flexibility in price-dependent bids. The price-dependent model turns off generator 1 for a number of scenarios in the hours between 20-24 and the early hours of 1-3 (Figure 5.7), and turn of both generators in one scenario (Figure 5.8). The price-independent model still leaves both generators committed throughout the whole bidding period.

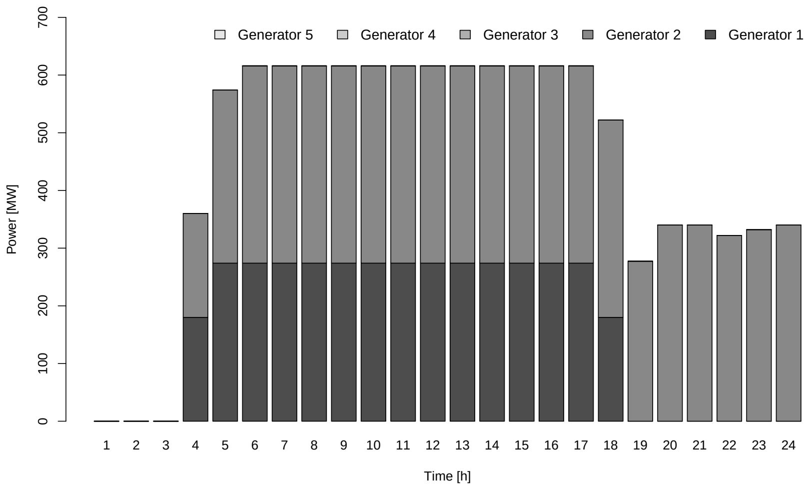

Figure 5.7: Example of production dispatch with price-dependent bidding for one specific scenario

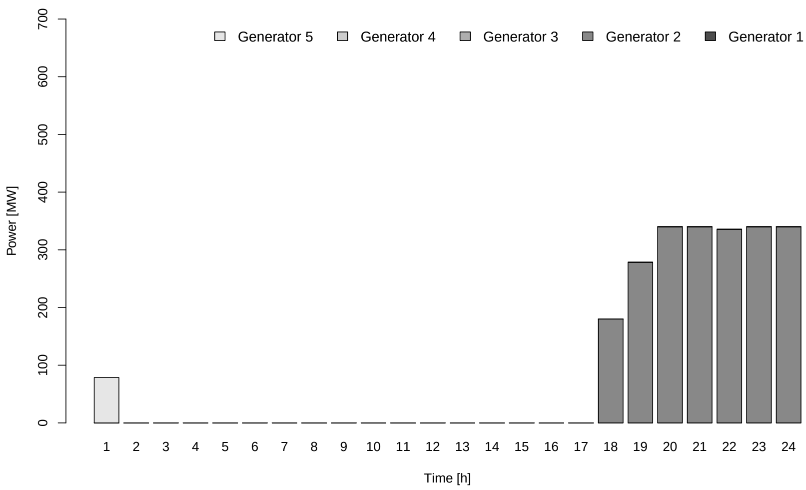

Figure 5.8: Example of production dispatch with price-dependent bidding for one specific scenario

5.3.2 Bidding strategies

The bidding curves from the price-dependent model shows a more varied structure where bids are made for a much larger variation of prices for all time steps. These bids should therefore be more robust against unexpected price scenarios. The bidding curves are reflective of the unit commitment decisions where units 1 and 2 are turned off in a number of scenarios. These unit commitment decisions corresponds with zero bids for a number of price points and times steps as seen in Figure 5.10. The variation of bids however is still all within the production range of unit 1 and 2 as the price level is still too low to activate more of the portfolio.

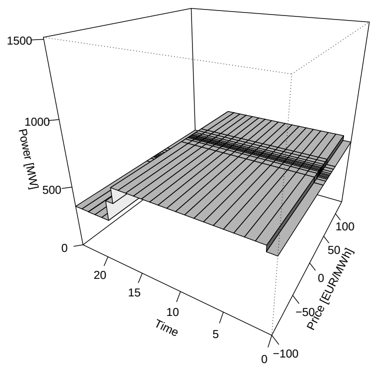

Figure 5.9: Bidding curves from the price-independent model in case 2

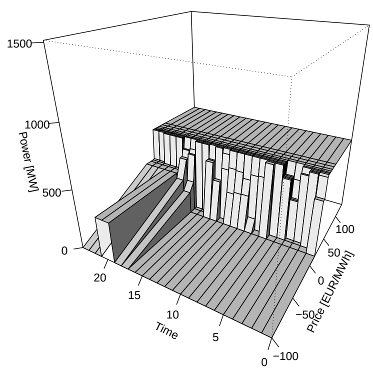

Figure 5.10: Bidding curves from the price-dependent model in case 2

5.3.3 Value of price-dependent bidding

The bids generated were tested against the same seven weeks used in case 1 in an out-of-sample test. The results in Table 5.5 and Table **??** show that when bids are generated for a large range of prices in all time steps the price-dependent bids outperform the price-independent model significantly, and increasing with the penalty level of the balancing market.

Table 5.5: Profit, VPDB and RVPDB with seven out-of-sample scenarios for fixed bidding decisions from both optimization models, with penalty of 0.5 EUR/MWh for the use of the balancing market

Scenario	Price-dep. bidding	Price-indep. bidding	VPDB	RVPBD
1	244326	244257	69	0.03 %
2	178385	178239	146	0.08 %
3	-6349.61	-6623	273,39	4.13 %
4	-5981.94	-6623	641,06	9.68 %
5	42119.4	41833.5	285,9	0.68 %
6	198635	198574	61	0.03 %
7	246137	245460	677	0.28 %
Mean	128181.6	127873.9	307.6	2.13 %

Table 5.6: Profit, VPDB and RVPDB with seven out-of-sample scenarios for fixed bidding decisions from both optimization models, with penalty of 10 EUR/MWh for the use of the balancing market

Scenario	Price-dep. bidding	Price-indep. bidding	VPDB	RVPBD
1	243421	243620	-199	-0.08 %
2	177496	176539	957	0.54 %
3	39187.8	35045,2	4142,6	11.82 %
4	-4030.29	-10345.2	6314.91	61.04 %
5	41230.5	39263	1967.5	5.01 %
6	198188	198404	-216	-0.11 %
7	245489	238424	7065	2.96 %
Mean	134426.0	131564.3	2861.7	11.60 %

5.4 Case 3: Historical data with artificial high prices

A market with artificial high prices was designed to be able to activate more of the generator portfolio and shed more light on the value of price-dependent bidding. As more generators are committed, the power producer will be able to utilize a larger ramping range and increased flexibility in production. To build on the results from case 2, the prices in the scenarios was shifted by an amount of 15 EUR/MWh to achieve a higher mean electricity price and make the prospects of using the higher cost generators more attractive.

5.4.1 Unit commitment problem

As more generators can potentially start and stop, this problem is extensively more complex than the two problems previously described. It was not possible to solve the optimization model in sufficient time. Running the proposed optimization model in section 3 produced 12 solution. By including the two cuts specified below (5.1) (5.2) it was possible to obtain a better bound with a mip-gap $< 1\%$. The cuts specify that units 3 and 4 will only be used if units 1 and 2 are already committed. This is given by the cost structure of the portfolio and was supported in the results from the two previous cases. The subsequent section is based on the best solution found in the price-dependent optimization model and the optimal solution from the price-independent model.

$$2 * u_{3t}^{s} = u_{1t}^{s} + u_{2t}^{s} \qquad s \in S, t \in T \qquad (5.1)$$

$$2 * u_{4t}^{s} = u_{1t}^{s} + u_{2t}^{s} \qquad s \in S, t \in T \qquad (5.2)$$

Generators 1 and 2 are always on both in the price-dependent and the price-independent model for all scenarios and time steps. Figure 5.12 shows that the price-dependent model activates the whole portfolio, starting and shutting down both generator 4 and generator 5. In Figure 5.11 the power producer is able to use the ramping range for all the generators to reduce production in time step 9 and satisfy the minimum run time restrictions.

5.4.2 Bidding strategies

The bidding strategies are shown in Figure 5.13 and Figure 5.14. The greater variation in the price-dependent bidding curves reflects the increased flexibility in the portfolio. This increased flexibility should ultimately make the price-dependent bids more valuable than in the previous case. The high volatility in prices leaves the price-independent model unable to justify the

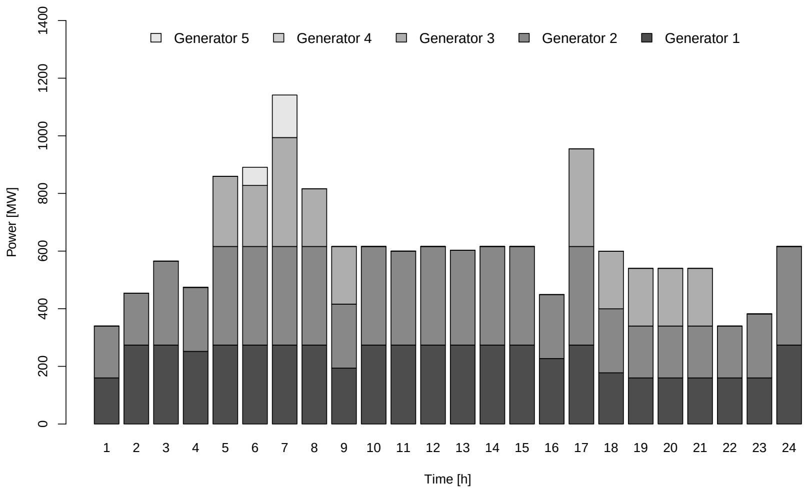

Figure 5.11: Example of production dispatch with price-dependent bidding for one specific scenario

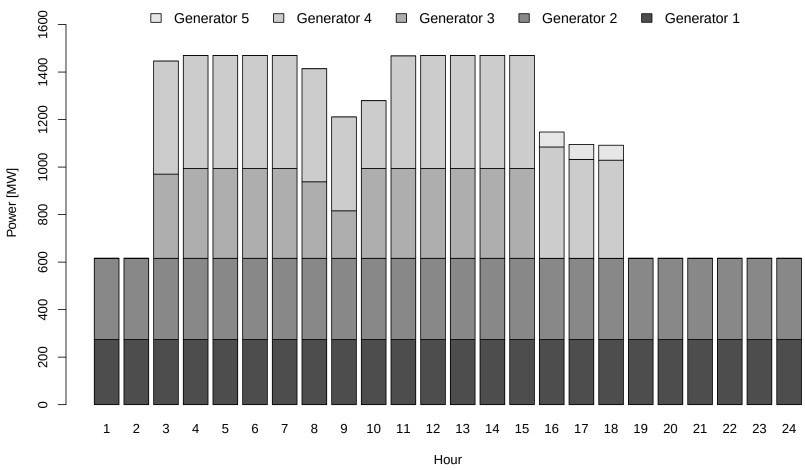

Figure 5.12: Example of production dispatch with price-dependent bidding for one specific scenario

commitment of more than unit 1 and unit 2. For these two units the maximum capacity bid is submitted for all time steps.

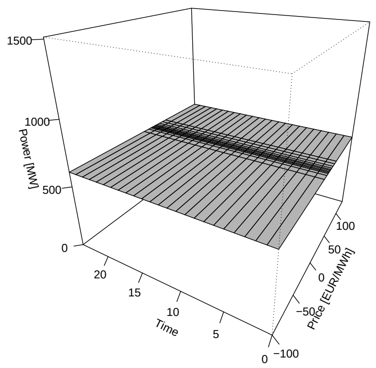

Figure 5.13: Bidding curves from the price-independent model in case 3

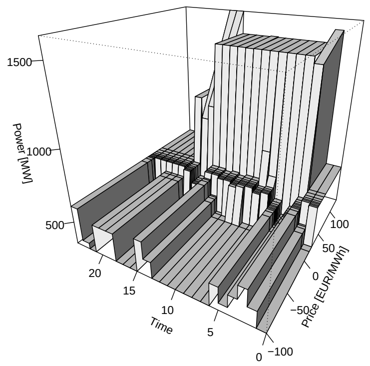

Figure 5.14: Bidding curves from the price-dependent model in case 3

5.4.3 Value of price-dependent bidding

The bids generated were tested through an out-of sample analysis using the same seven weeks as previously, but shifting the prices accordingly. The results did not confirm the assumption that the increased flexibility would increase the value of price-dependent bidding. As [17] has stated, price-dependent bids that are based on a number of committed units might leave the power producer unable to satisfy the market commitment or be left with an unprofitable market commitment. This results in the extensive use of the balancing market to obtain feasible solutions, or reduce the loss of suboptimal unit commitments. The results from the simulations show that the price-dependent model uses the balancing market to a much larger extent than the price-independent model. In this high priced market, the price-independent model is also able to reduce the losses of price-independent bidding by selling electricity in the balancing market for prices above marginal cost. Thus, the cost structure of this portfolio and the presence of a liquid balancing market reduces the differences between the two bidding strategies and makes the price-independent bids a preferable choice as seen in Table 5.7 and Table 5.8.

Table 5.7: Profit, VPDB and RVPDB with seven out-of-sample scenarios for fixed bidding decisions from both optimization models, with penalty of 0.5 EUR/MWh for the use of the balancing market

Scenario	Price-dep. bidding	Price-indep. bidding	VPDB	RVPBD
1	610501	611692	-1191	-0.19 %
2	431365	432230	-865	-0.20 %
3	221501	224080	-2579	-1.15 %
4	140123	140613	-490	-0.35 %
5	253196	254726	-1530	-0.60 %
6	494980	496626	-1646	-0.33 %
7	492085	493231	-1146	-0.23 %
Mean	377678.7	379028.3	-1349.6	-.44 %

Table 5.8: Profit, VPDB and RVPDB with seven out-of-sample scenarios for fixed bidding decisions from both optimization models, with penalty of 10 EUR/MWh for the use of the balancing market

Scenario	Price-dep. bidding	Price-indep. bidding	VPDB	RVPBD
1	474194	496166	-21972	-4.43 %
2	373763	388205	-14442	-3.72 %
3	176931	224080	-47149	-21.04 %
4	118015	229711	-111696	-48.62 %
5	225786	254726	-28940	-11.36 %
6	385685	418607	-32922	-7.86 %
7	438890	468798	-29908	-6.38 %
Mean	313323.4	354327.6	-41004.1	-14.77 %

Chapter 6

Discussion

It is the flexibility in providing multiple bids for each time step that differentiates the price-dependent and price-independent bidding strategies. In a world of perfect information, price-dependent bids would always outperform price-independent bids by having the flexibility of specifying bids for multiple price outcomes. The price-dependent bids relax the requirement that only one bid can be made for each time step as is the case with price-independent bids. However, when the assumption of perfect information does not hold, these results are not necessarily valid since thermal production dispatch is coupled in time. Unforeseen market events might leave the optimal unit commitment unprofitable or infeasible. The advantage of price-independent bidding in an uncertain world is the certainty that regardless of market outcomes the market commitment will always result in a feasible dispatch.

The object of this report has been to analyze the trade-off between flexible solutions and increased market risk by analyzing the two bidding strategies through three case studies. In these cases the flexibility in the problem was increased and the results from the two bidding strategies reviewed. The findings from these cases show that in a high-volatility market flexible bidding decisions are valuable as the power producer is able to reduce losses in the event of unexpected price drops and increase profits in the event of unexpected price peaks. However, they only contribute where the capacity of the system is sufficiently large. This is the situation in case 2 where bids are made on the basis of the commitment of two units. As most of the bids are based on the commitment of these two units, the power producer does not face the risk of a market commitment that would violate ramping restrictions and minimum run time and minimum down time restrictions. Thus, the power producer is able to obtain flexibility without introducing market risk. In case 3 a larger part of the portfolio of generators were activated and bids were generated based on a much larger variety of committed units. The results being, a potentially higher reward in flexible bidding decisions, but a larger risk in unwanted market commitments. The results from the case study show that in these circumstances the value of price-independent bidding is greater than the value of price-dependent bidding.

It is not just the market volatility and flexibility in the problem that influences the value of price-dependent bidding. The quality and accuracy of the price predictions and the scenario generation method ultimately determine the value of price-dependent bids. The low variation in the prices from the ARMA model generated bids that did not sufficiently take into account the variation in the market. Hence, these bids produced lower returns in the spot marked compared to bids that were generated using historical data. ARMA models have been shown to poorly predict prices in markets of high volatility [5]. Even with a decent price forecasting tool it might be necessary to include highly unlikely extreme scenarios to obtain bidding decisions for these events. It is in these extreme scenarios that price-dependent bidding has the most value (see Table 5.6).

In this report, the balancing market was modeled as a penalty function where both sales and purchases were penalized. This was done to avoid planned imbalances as part of the bidding decisions. The penalty was set as a fixed deviation from the realized market price, and the bidding decisions sensitivity to this penalty was analyzed. This is a simplified formulation of the use of a balancing market. In [22] both the spot market, the balancing market and the reserve market is explicitly described in a multistage problem. These problem extensions could have provided additional insights into the optimal bidding strategies. The dependency between the balancing market and the optimal bidding strategies is not a simple linear relation. As the penalty increases the optimal bidding strategy may change as seen in Tables 5.5 and 5.6. The influence of the balancing market might significantly impact the optimal bidding decisions as it is the access to a liquid balancing market that ensures the fulfillment of the market commitments.

The characteristics of the generators will influence the flexibility and thus the value of price-dependent bidding. The case-studies show that units with long up-time and down-time restrictions are likely to run constantly. Flexible units can have a more diverse dispatch pattern given that the prices are high enough to justify their commitment. For power producers with a high proportion of flexible units price-dependent bidding might be more relevant.

Chapter 7

Conclusion

The bidding problem is complex and a variety of factors influence the optimal choice of bidding strategies. The nature of the balancing market, the quality of the forecasting tool and the market structure has been identified as factors that affect the optimal bidding strategy. Without an appropriate price forecasting tool the value of price-dependent bidding is reduced as the bids are constructed based on inadequate or incomplete information. This leaves price-dependent bids vulnerable to market events the forecasting tool is not able to predict. The implication is that thermal power producer should only consider price-dependent bidding when they are confident in their forecasting.

Using historical price data it was possible to generate price-dependent bids that more accurately incorporate the price variation. These bids outperform the price-independent bids as the power producer is able to reduce losses in low price scenarios and increase profits in high price scenarios. The drop in mean electricity prices in the German-Austrian market has increased the chances of prices falling below marginal costs of generators and low price scenarios might make it optimal to turn off generators rather than leave them running through the whole bidding period. Thermal power producers trading on EPEX SPOT might reduce losses and increase profits by incorporating some of the ideas presented in this paper to construct price-dependent bids.

The value of price-dependent bidding was assumed to increase with increased flexibility in production. However, with a larger number of units committed the risk of infeasibility increases significantly. This is because a high variation in prices might result in large differences in production dispatch from one hour to the next. To compensate for infeasible solutions the power produces use the balancing market extensively. The results indicate that the risk of infeasible solutions outweigh the potential gains from price-dependent bidding. In these circumstances power producers should utilize price-independent bidding strategies to obtain the highest profits in the spot-market.

Through three case studies the authors have quantified and examined the value of price-dependent and price-independent bidding in the spot market. Both price-dependent and price-independent strategies have been discussed in the literature, but the two strategies have not been compared directly in case studies. The findings of this project indicate that there is still reason to believe that both strategies are relevant for thermal power producers.

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