PARAMETRIC SENSITIVITY STUDY FOR
WIND POWER TRADING THROUGH
STOCHASTIC RESERVE AND ENERGY
MARKET OPTIMIZATION

Dissertation in partial fulfillment of the
requirements for the degree of

MASTER OF SCIENCE WITH A MAJOR IN
ENERGY TECHNOLOGY WITH FOCUS
ON WIND POWER

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Abstract

Trading optimal wind power in energy and regulation market offers possibilities for increasing revenues as well as impacting security of the system in a positive way[33]. The bidding in both energy and regulation markets can be done through stochastic optimization process of both markets.

Stochastic optimization can be possible once the probabilistic forecast is available through ensemble forecast methodology. For stochastic optimization, the post-processing of the ensembles to generate quantiles that will be used in optimization can be accomplished by employing different methodology. In this study, we will concentrate on the impact of post-processing of ensembles on the stochastic optimization.

Generation of quantiles needed for stochastic optimization used herein for market optimization will be the main focus of the investigation. The impact of price ratios between energy and reserve market will be also investigated to analyse the impact of said ratios on the revenues. Furthermore this analysis will be performed for both US and Swedish markets.

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Nomenclature

π	Price of energy
π_{E+}	Price for over provision of energy
π_{E-}	Price for under provision of energy
π_{UR+}	Price for over provision of up regulation
π_{UR-}	Price for under provision of up regulation
P_{cE}	Committed Energy
P_{cUR}	Committed Up Reserve
P_c	Committed power
P_t	Actual power production
P_{tmax}	Installed capacity of wind farm (max production)
R_E	Revenue from regular energy market
R_{UR}	Revenue from up regulation
ACE	Area Control Error
AGC	Automatic Generation Control
CAISO	California Independent System Operator
CR	Competitive retailer
DAM	Day Ahead Market
ENTSO-E	European Network of Transmission System Operators for Electricity
ERCOT	Electric Reliability Council of Texas
FCR	Frequency Containment Reserve
FERC	Federal Regulatory Commission
FRR	Frequency Restoration Reserve
ISO	Independent System Operator
ISO-NE	ISO New England
LSE	Load serving entity
MISO	Midcontinent Independent System Operator
NERC	North American Electric Reliability Corporation
NordREG	Nordic Energy Regulators

NYISO	New York Independent System Operator
PJM	Pennsylvania-New Jersey-Maryland Interconnection
POLR	Provider of last resort
QSE	Qualified scheduling entity
RSS	Residual Sum of Squares
RTO	Regional Transmission Operator
SPP	Southwest Power Pool
SvK	Svenska Kraftnät
TSO	Transmission System Operator

1. Introduction

Imbalances between load and generation creates the need for regulation. The services that help provide reliable energy supply are called *ancillary services* and help regulate some fundamental properties of the grid. The Transmission System Operator (TSO) or Independent System Operator (ISO) must have contractual agreements to use these when they are needed to keep the system stable. There is no world-wide terminology that are used and sometimes different names are utilized with similar technicalities across borders. However, the reference [32] summarizes the main categories as follows: voltage control, frequency control, reserves, load following, black start, losses and load shedding.

Variations in demand and supply of power arise due to several factors such as normal daily routines as well as grid changes due to temporary line faults. Lightning strikes are a common environmental cause for line faults [24, 13]. For the Nordic countries, [13] reports other environmental causes for line faults and includes non-environmental categories for causes. Figure 1.1 shows one of the most common frequency deviations that occur daily due to changing loads. These hours of the day are called the ramping hours, when consumers increase or decrease consumption collectively.

Additionally to the previous forms of unexpected variations, wind power production itself is difficult to schedule due to its stochastic nature and inherent forecasting inaccuracy despite state-of-the-art technology, having a negative effect on grid stability and balancing requirements. [20, 37, 21] In order to maintain an acceptable quality of delivery these variations need to be addressed accordingly.

Historically, the energy grid has been mostly set up in a centralized scheme where large generator stations feed the transmission lines that carry this power to distribution stations in order to reach all the consumers. This is also known as a vertically integrated utility or company [32, 7]. In this structure, all of the generators are centrally controlled and all power control mechanisms are an integrated part of the business and this control mechanism simply represented an additional operational cost [32]. In a deregulated system these services become business opportunities and therefore have a marketable value.

The first section of the investigation describes how the two observed electricity markets operate. United States and Sweden are compared for similarities and differences in terminology and characteristics. The following section describes several types of methods for wind power forecasting. It covers in greater detail the regression methods used for their comparison in simulations.

(a) Frequency violations in morning hours [12]

(b) Ramping hours are highlighted [11]

Figure 1.1. Frequency deviations during ramping hours

The input values and their source are explained for each method. Resulting quantiles are graphed for visual comparison and to have a clearer picture of the significance. Next, a bidding algorithm is selected and explained in terms of necessary input values and its operation. A base scenario for revenue in United States market is simulated where the power provider only bids in energy market with the point forecast. This revenue is compared to the resulting revenue from using the bidding algorithm with the regression methods previously explained to compare their performance. Finally, the bidding algorithm is applied to the Swedish market. A parametric study is carried out to observe how different price levels affect revenue in this market, only using one quantile generation method.

2. Literature Review

2.1 Electricity market in United States

The United States began restructuring the electricity markets starting from 1996 with Federal Regulatory Commission (FERC) orders 888 and 889 due to elevated prices. Each state established its own market rules and its transition to a deregulated power market [7], however, FERC proposed a common design for wholesale of electricity in [6] establishing a '*two-settlement system*.' This system encompasses two parallel markets, the day-ahead market and the real-time energy market, both of which use locational marginal pricing. FERC, however, did not specify the procurement for ancillary services in this proposal[9].

2.1.1 Market participants [16, 35, 17, 38, 9]

There are seven RTO/ISO regions in United States to date: California ISO (CAISO), Electric Reliability Council of Texas (ERCOT), Southwest Power Pool (SPP), Midcontinent Independent System Operator (MISO), Pennsylvania-New Jersey-Maryland Interconnection (PJM), New York ISO (NYISO), and ISO New England (ISO-NE). Each one is regulated by FERC except ERCOT which is out of its jurisdiction; however all follow FERC recommendations [16]. Although many ISOs share similar names for market participants, this paper will cover ERCOT's market due to the data being used. The relevant market participants are listed below:

Independent System Operator (ISO) performs the function of a System Operator, where it oversees system reliability, and of a Market Operator where it manages the 'power pool' and exchanges between market players. [38] It is independent and does not own transmission, generation or distribution. A Regional Transmission Operator (RTO) acts similarly concerning matters of marketplace for exchanges and system security.

Qualified scheduling entity (QSE) is a market participant, a generator(cite), qualified by ERCOT to schedule and provide ancillary services when needed. It must have an operating scheduling center 24 hours a day or every day with the authority to dispatch necessary resources. One QSE may be split into subordinate QSE which may be treated individually but must share communication, liability, financial security and financial

liability requirements.

Resource entity (RE) an entity that owns or controls a generation¹ or load² resource. A generation entity is a resource entity.

Load serving entity (LSE) is an organization that is obligated to provide power to retail customers, a form of distribution[9, p.20]. These secure energy and transmission service along with reliability services for end users. They submit load profiles, characteristics, plans and forecasts to balancing authorities, purchasing-selling entities, planning coordinator, resource planners and transmission planners. Meanwhile they also manage reliability service commitments.

Competitive retailer (CR) also a LSE, is a municipally owned utility or electric cooperative that sells electric energy at the retail level providing consumer choice.

Provider of last resort (POLR) is a local distributing company for either residential or non-residential customers who do not have a retail electric provider.

Transmission/distribution service provider (TDSP) is an entity that provides transmission or distribution services or has been selected to own and operate transmission facilities.

2.1.2 Ancillary services

FERC defines six mandatory ancillary services: reactive power, frequency control, reserves, load following, black start, losses and load shedding. [32, 23] Of these, only frequency control and reserves will be investigated in this thesis.

The North American Electric Reliability Corporation (NERC) defines a number of frequency and balance controls [40] and also differentiates between different types of reserves.

The nomenclature for a similar service, if not the very same, differs across the USA in each ISO. Table 2 of [9, p.14] summarizes these similarities well identifying three frequency control categories throughout USA: primary, secondary and tertiary. This investigation, however, compares only ERCOT's service scheme for frequency control and balancing:

¹Generator capable of providing energy or ancillary service

²A load capable of providing ancillary service

Primary frequency control is used to arrest the effects of sudden frequency changes. Generators have independent *governor control* which is what reacts to frequency dips. This is a local, automatically activated control mechanism. In simple generator designs the governor is a mechanical device which maintains generator speed by regulating the power output whereas more complex designs may involve automation and electronics. This control reacts much quicker to frequency drops than other system-wide controls [40] Deadband is the threshold in system frequency where governor control will not activate, beyond this threshold governor control will kick in to respond to frequency deviations. This is usually 0.036Hz above or below nominal frequency of 60Hz. Machines with a mechanical governor device may have a wider deadband. This service is not marketable in ERCOT, however it is a required capability.[40]

Secondary frequency control consists of automatic and manual actions to maintain system balance and is controlled centrally by each RTO/ISO by evaluating the *Area Control Error* (ACE). ACE compares the real-time energy flows to the scheduled energy transactions; a difference would indicate a surplus or shortage of generation. *Automatic Generator Control* (AGC) is the mechanism that controls generator output using signals which are relayed externally by the RTO/ISO to each participating generator in the control area. This frequency control is meant to relieve primary control and prepare for the next contingency or event. In ERCOT it is a marketable service called *regulation services*.

Tertiary frequency control will relieve the previous activation of secondary control reserves until balance is restored while it prepares for the next contingency. It is called *responsive reserve service* in the ERCOT market and in other markets may be known as *spinning reserve*.

Load following is used to "follow the general trending load patterns within the day" [9]. It is an automatically activated service to balance differences in load and generation. It works closely to frequency control. This service is usually provided by spinning reserves, which in turn also provides *tertiary control*. One may observe that a generator may have the ability to provide more than one type of support service for the system.

2.1.3 Trading ancillary services

Each ISO/RTO procures these support services differently, usually both day-ahead and during the operating day. This may be done either by decoupled, coupled or integrated co-optimization of energy and ancillary services. Integrated co-optimization means that all energy and ancillary services are op-

Table 2.1. *Summary of market conditions in ERCOT [9]*

Market pay-out	
Energy market	Marginal
Ancillary services	Marginal
Bidding times	
Energy market	00:00 - 10:00 day before operation
Ancillary services	00:00 - 10:00 day before operation
Adjustment (all)	18:00 day before until operating hour

timized considering all constraints imposed on the system at the same time whereas decoupled co-optimization runs two parallel optimizations for energy and ancillary without imposing constraints on each other [9, 26].

This investigation will focus only on the Texas market so only ERCOT will be considered. ERCOT uses integrated co-optimization for the day-ahead market (DAM) and coupled co-optimization during real time operations during which energy and ancillary are optimized separately but include system constraints. According to forecasted demand, ERCOT establishes how much ancillary capacity must be made available by Load Serving Entities (LSEs) and Qualified Scheduling Entities (QSEs). QSEs may provide any or all of the ancillary services simultaneously.

For energy demand and supply, offers for bids in energy, regulation, responsive reserve, and non-spinning reserve for each hour of the day are submitted to the DAM from 00:00 until 10:00 of the day before operation (D-1)[9]. The market clearing process begins at 10:00 and determines hourly commitments for both energy and reserve. There is an *adjustment period* that begins at 18:00 the day before the operating day during which QSEs may correct any commitments for any hour of the operating day until the hour in question. Co-optimization allows for offers of different services to be submitted at the same.

As explained in [39, p.22], each market in a different time-frame is a residual market of the previous one. For example, bilateral contracts are agreed upon much earlier than when day-ahead bids are considered. Day-ahead transactions can only consider the remaining available power generation after bilateral contracts, hence this is a residual of the bilateral market. Like so, the available reserves are only those watt-hours that have not been committed in the previous markets.

2.2 Electricity market in Sweden

The Swedish electricity market has been deregulated from 1996, allowing for energy producers to sell either directly to the consumer, the power pool or an energy trader and any other combination between any of the participants. This

Figure 2.1. Bilateral trading

is called bilateral trade, figure 2.1 shows these trading relationships. Consequently, ancillary services in this market are not an integral part of the energy provision and are sold separately. The Transmission System Operator (TSO) in Sweden is Svenska Kraftnät (SvK) and it is the one responsible for maintaining the transmission lines and grid security while acquiring the aforementioned services from various providers.[27]

2.2.1 Typical stakeholders in Swedish electricity market [27]

The Swedish Energy Markets Inspectorate oversees the energy markets in Sweden and is a member of a Nordic cooperation called *Nordic Energy Regulators* (NordREG), and *Agency for the Cooperation of Energy Regulators* (ACER) for Europe. Aside from the regulatory organizations, the relevant participants in the Swedish electricity market are:

Electricity Producers such as generators and power stations can sell their energy either directly to consumers, traders or power exchange. Most of the time it is sold to the spot market at the power exchange, Nordpool.

Power trading companies buy power from producers directly or from the power exchange to later sell to consumers. These are electricity suppliers who have commercial agreements with consumers.

Balance providers have agreements with SvK. Power producers or suppliers may both provide balance power service while producing power. SvK purchases this service from the balance providers when needed to stabilize the grid.

Grid operators own the regional and local grids. Regional grids are in the range of 40kV – 130kV while local grids are 40kV or lower. A regional grid connects between national and local grids, sometimes directly from national grid to large consumers such as heavy industry. Local grids

distribute power to smaller consumers. SvK manages the national grid which includes transmission lines, substations and international connections. It is the TSO and needs to ensure grid reliability at a national level and that energy production and imports match consumption and exports. GEAB is the local grid operator on the island of Gotland. E.ON Elnät Sverige, Vattenfall Eldistribution and Fortum Distribution are a few of the largest local grid operators who operate in mainland Sweden.

Consumers are those who use the power service. These, such as households and factories, have a contract with the chosen supplier and another with the grid operator to allow them to connect to the grid. Each participant pays a fee for the transmission of electricity.

The Exchange Market is run by Nordpool and allows for standard agreements between market participants to do business with each other. Nordpool has a spot market that is traded on an hourly basis also known as the intra-day market and is called Elbas. This market is used by market participants to make corrections to their day-ahead bids.

2.2.2 Ancillary services

Sweden has three categories of ancillary services and has adopted the ENTSO-E³ nomenclature for some of the services since 2014.

Frequency Containment Reserve (FCR) , categorized under the *automatic active reserve* in [15], is a form of active power control because it regulates frequency by keeping the power in balance when there are sudden changes in load or generation. This reserve is automatically activated at the local generator by the system frequency deviation. It is meant to stabilize the system frequency in the short term, not correct imbalances in the system [14]. This activation does not need to be centrally controlled by SvK since frequency is a system-wide property. *Frequency containment reserve in normal operation* (FCR-N) is activated when there are mild deviations in the system while *frequency containment reserve in disturbed operation* (FCR-D) is activated when frequency deviates further. Hydropower is the main power source for this service [31].

Frequency Restoration Reserve (FRR) also uses active power however it is meant to correct for imbalances and restore the system frequency to the set point of 50Hz. This service is activated centrally by the TSO [14]. SvK's remote activation constitutes an automatic and manual operation where the automatic activation is similar to load frequency control (LFC) [3] in that it balances changes in load such as during ramping hours .

³European Network of Transmission System Operators for Electricity

Table 2.2. *Summary of market conditions in Sweden [30]*

Market pay-out	
FCR-N/D (Primary regulation)	Pay-as-bid [30] \$6.3
FRR-A	Pay-as-bid [30] \$6.5
FRR-M	Marginal pricing [29] \$5.1
Bidding times	
FRR-A bid submit time	On Thursday at 10.00 for coming Saturday-Friday period [30] \$4.3
Primary bid submit time (D-1)	18.00 day before [30] \$3.4
Primary bid submit time (D-2)	15.00 two days before [30] \$3.3
FRR-M (Regulating reserves)	12:00 day before [36]
Peak load reserves	16 november - 15 march [30] \$7

Peak Load Reserves is a type of service that is used for the same purpose as frequency control and load balancing but used in distinct circumstances. Reserves are typically used for generator outages or large disturbances to keep the system at equilibrium. SvK purchases special reserve capacity for winter because of increased demand for heating and does not allow for these providers to participate in the spot market since their additional costs are compensated. These reserves may be in the form of additional production capacity or demand response, a form of *load shedding* and are activated manually by the TSO. This reserve capacity is contracted between the 16th of November in one year and 15th of March in the following year [30].

2.2.3 Trading the ancillary services

SvK defines five balance services as described previously: FCR-N, FCR-D, FRR-A, FRR-M and peak load reserves. Bids are sold in two day-ahead markets, D-1 and D-2, which are one and two days advance bids – respectively. Each one has a different closing hour, 18:00 and 15:00. FRR-M is traded through Nordpool and uses the marginal price to set the price for all providers while FCRs and FRR-A is handled directly with SvK using the pay-as-bid method. FRR-M prices and volumes are publicly available on Nordpool’s website. The closing hour in Nordpool is at 12:00 before delivery day. Providers are not allowed to withdraw their accepted bids after gate closure but may re-purchase them at the marginal price. Balance responsible players need to additionally pay a fixed monthly fee of 1 850 SEK. ([30] \$6.10.2)

All commitments are paid before the operating hour since they are contractual agreements. However the ancillary payments and penalty invoicing occurs after the operating hour, and it is called the settlement period. Penalties for imbalances depend on the system state: if the TSO needs to procure up-regulation then it is in an up-regulation state. Similarly, if the TSO needs to

procure down-regulation then it is in a down-regulation state. This constitutes a two-price system.

As an example for an energy provider, the over-provision of committed energy may have two outcomes and will depend on the system status. If the system requires up-regulation, the extra energy provided will not be penalized because it helps with up-regulation procurement and will be paid at market price for that hour and not rewarded with the up-regulation price. If the system requires down-regulation, then the extra energy will be paid at the down-regulation price which is lower than the market price which constitutes a penalized price.

As an example for the case of a balance service provider, if the balance provider is providing adequate balance service in down regulation it means it is producing less than the committed energy in the normal day-ahead market and in so doing it buys back the energy it had already sold (contractual agreement) before the operating hour at a lower price, the down-regulation price, rewarding the balance provider with a profit. However if this balance service provider does not support the system then this 'over production' of energy will be paid at the down regulation price. Since it is marginal pricing system for this kind of balance power, this provider's down-regulation price is better than the next provider's price, and since this one could not provide, it will have to sell this power at the price of the one which did provide the service at an even lower price.

Generally, the energy provider who produces an imbalance pays for the one who provides for the balance service to support the system; however the provider is not rewarded extra revenue when its deviation from commitment helps the system. The balance provider that provides the committed balance will be rewarded with a better price. These balance settlements with marginal prices regard only to FRR-M or tertiary reserves traded in Nordpool; other ancillary services do not benefit from marginal pricing. See table 2.3 for a summary of this two-price system.

2.3 Similarities

This investigation focuses on the services that agree with the time-scale of the power forecast, delivery and bidding data as well as function in both countries. The services that are considered here are USA ERCOT's secondary frequency control service or *Regulation Service* and Sweden's *Frequency Restoration (Automatic)* control. Both are activated centrally by the system operator, have separate market and commitment operations. The market rules differ but the service each provides is comparable. Frequency triggers will activate the services in merit-order basis as long as it is technically permitted.

⁴Up-regulation

⁵Down-regulation

Table 2.3. *Summary of penalties*

<i>For energy producers</i>		
System status	Over production of commitment	Under production of commitment
Up-regulation hour	Sell at market price	Invoice for undelivered power with UR ⁴ price
Down-regulation hour	Sell at DR ⁵ price	Producer buys back at market price
<i>For balance providers</i>		
System status	Provide balance	Increase imbalance
Up-regulation hour	Sell at UR price	Invoice for undelivered power with UR price
Down-regulation hour	Buy at DR price	Sell at DR price

Table 2.4. *Comparable reserve characteristics*[3, 31, 14, 12]

USA (ERCOT)	Activation (freq.)	ENTSO-E / SvK	Activation (freq.)
Primary Frequency Control	Auto (59.964-60.036)	FCR-N FCR-D	Auto (49.9-50.1) Auto (49.5-49.9)
Secondary/Regulation ⁶	Signal from ERCOT	FRR-A	Signal from SvK
Tertiary ⁶	Signal from ERCOT	FRR-M	Signal from SvK

⁶Differences in equivalent nomenclature for FRR services in sources.

3. Methodology and Data

3.1 Stochastic uncertainty estimation theory

The cost impact of forecast errors have been found to be largest in the day-ahead scheduling as compared to regulation time-frame [2]. Increasing amounts of wind power penetration in electrical grids makes research in wind power forecasting all more valuable. Although larger participation of wind energy can reduce overall emissions [8], it calls for more precise wind power predictions in order to minimize impacts on grid stability, security, optimal power flow calculations and unit commitment scheduling operational costs.

There are different methods of forecasting. These methods are generally classified depending on the method, input data, and time-frame. These methods have an optimum time horizon for predictions and the choice would depend on the purpose of the application. There is no unanimous label for time horizons but may be generalized as: very short, short, medium and long-term. Globally and locally the further the prediction, the larger the inaccuracies because of the sensitivities of the weather systems to initial conditions. Based on the following references [34, 46], the short term time horizon estimations seem to oscillate between 48 and 72 hours and medium term covers 1 week ahead forecasting. Table 3.1 depicts these time brackets and their use.

In this study, we will give a short summary of stochastic estimation methods. Probabilistic forecasts of wind energy generation are of high financial importance for wind power industry players to assess the financial risk. Such forecasts can be based on forecast ensembles from numerical weather prediction models which is discussed shortly in the next subsection [47] [42]

Table 3.1. *Time frames in WPF*

Time Horizon	Range	Application Purpose
Very short term (minutes-hours)	Up to 30 min ahead[34] Up to 9 hrs ahead[46]	<ul style="list-style-type: none"> • Electricity market clearing[34] • Wind turbine control[34] • Ancillary services[46]
Short term (hours)	Up to 48 or 72 hours ahead[34, 46]	<ul style="list-style-type: none"> • Economic load dispatch planning[34] • Load increment/decrement decisions[34] • Trading[46]
Medium term (days)	48 or 72 hours to 1 week ahead[34, 46]	<ul style="list-style-type: none"> • Generator online/offline decisions (arrangements for maintenance)[34, 46] • Unit commitment decisions[34, 46]

[43] [44] [41] Probabilistic forecast methods can use ensembles to define the probability of the weather or atmosphere. Ensembles are different possible states in the atmosphere at a certain time. Once ensembles are generated through ensemble forecast system, it is possible to address the risk via quantiles by post-processing ensemble data. In this study, we will concentrate on the post-processing of ensembles impact on the stochastic optimization of both reserve and energy market for power system[33]. Generation of quantiles needed for stochastic optimization used herein for market optimization will be investigated through deterministic forecast data preliminary. This is to make our comparison consistent with the previous work in literature [33]. The ensembles forecasts discussed in the next subsection will be more statistically and physically complete way of using available information through usage of observations and weather forecast models [47] [42] [43] [44] [41] and this approach has not been pursued since this is beyond the scope of this work.

3.1.1 Theory of generation of quantiles through ensemble of forecasts

The majority of tools provide point forecasts which are given as only one measurement of the predicted power output. A more useful result is a probability forecast which quantifies the uncertainties of the predictions of the regional context. Probabilistic wind forecast system of are often based on ensemble prediction systems that can use micro scale or mesoscale weather forecast models. [47][42][43][44]. Numerical weather prediction (NWP) models are run with different initial conditions or different physical models to generate the uncertainty in the forecast to improve predictions. The ensemble forecast algorithms are of special interest due to their simplicity of implementations to other applications where adjoint operators are required. Their potential for efficient use on parallel computers with large-scale geophysical models is another advantage.

The ensembles that are generated through ensemble methods will need to be post-processed afterwards in order to make use of all information available in an ensemble forecast. Ensembles consist of several deterministic forecasts. However as it is the case in this work as discussed in the subsection, it is possible to generate approximate ensembles through single deterministic forecast. It is also possible to create ensembles by use of the variance margin of a single deterministic forecast in the employed time series as used in the paper[33] [4] [45]. One commercial tool, for example, called Wind Power Prediction Tool (WPPT) uses three methods for uncertainty estimations through Adaptive variance estimation, ensemble based quantiles, and quantile regression[10].

Figure 3.1. VARIANCE - Observed production and its variance plotted to the forecasted power. All the variables are normalized to installed capacity. Perfect prediction would render a 1:1 ratio and therefore a perfectly diagonal line.

3.1.2 Methodology of generation of quantiles through single deterministic forecast

In this study, single deterministic or point forecast variance margin of the employed time series will be used to generate the time series [33]. Several post processing techniques through definition of parametric distributions or quantile regression exist for ensembles based on quantiles that are generated through this approach. Ensembles may be jointly described with a probability distribution function that is well-known and easily parametrized. Two of the parametric distributions that will be studied are the *normal* and *beta* distributions. Quantile regression will be also investigated. The results may be presented as probability mass functions (*pmf*), quantiles, probability density functions (*pdf*), cumulative distribution functions (*cdf*), or with distribution descriptors such as mean, variance, skewness, kurtosis [34].

Generation of quantiles from point forecast with parametric distributions

To generate probability quantiles from the available time series, one investigated approach is the one employed by [33] used by calculating variance for various power classes, as explained in [4]. Variance of a dataset is defined as:

$$\text{Var}(X) = E[(X - \mu)^2] \quad (3.1)$$

The variance for every 0.05 step in the normalized power range constitutes one variance value for the mean power in that bracket. As can be seen in figure 3.1 This means that for a range (0,0.05), the variance of this range is represented at $\frac{0+0.05}{2} = 0.025$ normalized power, and for the (0.05,0.1) range, the variance is represented at $\frac{0.05+0.1}{2} = 0.075$. Figure 3.1 shows the calculated variance plotted across the power range. Variance is a non-negative value, therefore the resulting quadratic fit cannot give negative values. A contingency for variance as variance σ being y and $y \geq 0$ is set for the fitting since variance may have a zero value, indicating no variance; all values at that point are equal. The figure also shows the resulting fit.

Normal Distribution

A normal probability density function (*pdf*) is directly defined by the two parameters μ and σ , where μ is defined as the most probable forecast outcome (the point forecast) and σ is the variance calculated from the given data-set. The *pdf*, however, is valid beyond a wind farm's operating range. The function within the valid domain is hence normalized to the total probability within it. This cumulative distribution function has a range of ($F(x), x \in [0, 1]$), but its domain poses the same issue as the *pdf*, so it must also be normalized for the valid domain, shown in figure 3.2. The normal probability density function (3.2) and the normalized CDF (3.3) below:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \quad (3.2)$$

$$F_n(x, \mu, \sigma) = \frac{\frac{F(x, \mu, \sigma)}{F(1, \mu, \sigma)} - F(0, \mu, \sigma)}{1 - F(0, \mu, \sigma)} \quad (3.3)$$

Beta Distribution

The normal distribution is easily defined by mean and variance computed from a data-set, and [4] finds that beta distributions may be defined using these descriptors and used with satisfactory results. [18] also uses this distribution to assess the cost of prediction errors in wind. The following equations represent the mean and variance of the distribution [25]:

$$E[X] = \mu = \frac{\alpha}{\alpha + \beta} \quad (3.4)$$

$$\text{var}[X] = \sigma^2 = \frac{\alpha\beta}{(\alpha + \beta)^2(\alpha + \beta + 1)} \quad (3.5)$$

Figure 3.2. Normalized normal CDF - There are two cases of point forecasts shown, 0.025 and 1. These are considered mean values of the pdf, one of the inputs needed to define the shape of the pdf. a) is The resulting probability curve for 0.025 point forecast. b) is for point forecast of 1. The green line shows the resulting normalized curve.

The above expressions (3.4),(3.5) may be solved to obtain the α and β parameters of the distribution as such:

$$\alpha = \frac{(\mu^2 - \mu^3 - \mu\sigma^2)}{\sigma^2}, \beta = \frac{(\mu - 2\mu^2 + \mu^3 - \sigma^2 + \mu\sigma^2)}{\sigma^2} \quad (3.6)$$

The above expressions are used to define the beta distribution function [22]:

$$f(x) = \frac{x^{\alpha-1}(1-x)^{\beta-1}}{B(\alpha, \beta)} \quad (3.7)$$

A fundamental issue may be observed in the expressions for α and β when mean values take any of the lower or upper extremes (0 or 1) in that it renders invalid parameters since the Beta function is only supported while $\alpha, \beta > 0$ [1]. Moreover, the variance from the quad-fit may result in invalid parameter evaluations for predictions when approaching the upper limit; for the dataset used in this investigation it begins around $\mu = 0.94$. To remedy this obstacle, the normal distribution is used with normalized data when estimated beta parameters are invalid, resulting in a hybrid distribution algorithm. Part of the normal probability density falls beyond the bounds of the beta function ($\beta(x), x \in [0, 1]$) and the valid portion is hence normalized as mentioned previously. Figure 3.3 shows where the quantiles are truncated due to this set back.

3.1.3 Generation of quantiles through regression

Quantiles, another name for percentiles, are a way of representing the distribution of a dataset and assess the error. The median would indicate that 50%

Figure 3.3. Quantiles 0.05,10,20 ... 90,95 for the beta-normal hybrid

of the data points lie above this value and the other 50% lie below it. In this application, the 50th quantile would define that 50% of the data points lie below this point. In this dataset there is a 50% probability to attain a value at this point or below it. To clarify, this does not mean there is a 50% probability of attaining this number exactly as would suggest a probability distribution.

As explained by [28], classical linear regression makes use of least squares estimation to estimate the parameters of the linear model that best fits the data points. Quantile regression, then, also uses this method to estimate models for the desired conditional quantile functions. For one-dimensional data, the mean is defined as the minimization of the sum of squared residuals (also known as *residual sum of squares* - RSS) whereas the median is the minimization of the sum of absolute residuals. The following expression shows how a function may be estimated by use of RSS where $f(x_i)$ is the predicted value of the function and y_i is the value that will be predicted.

$$\min \sum_{i=1}^n (y_i - f(x_i))^2 \quad (3.8)$$

For quantiles however, the sum of absolute residuals is used instead of the squared residuals. Therefore:

$$\min \sum_{i=1}^n (y_i - f(x_i)) \quad (3.9)$$

In order to find the median, equal amounts of negative and positive residuals are needed. As a result, a quantile implies an uneven amount of each and thus may be calculated by assigning different weights to positive and negative residuals for values that are above or below the target. This differentiator, ρ_τ , called the tilted absolute value function, will determine the τ^{th} quantile. The expressions below show ρ_τ and a more explicit version depicting how it accomplishes to place different weights:

$$\min \left[\underbrace{(\tau - 1) \sum_{y_i < q} (y_i - f(x_i))}_{\text{values greater than } y_i} + \underbrace{(\tau) \sum_{y_i \geq q} (y_i - f(x_i))}_{\text{values less than } y_i} \right]$$

[28] proposes using linear programming methods to solve this minimization problem, so long as $f(x)$ is expressed as a linear function of parameters.

The forecast and observation data used for this study is taken from National Renewable Energy Laboratory's (NREL) *updated* Eastern Wind Integration and Transmission Study (EWITS) dataset. The 2006 year data for simulated wind farm site # 0195 is used to generate the forecast probabilities. AWS Truewind LLC was assigned the task to generate this extensive dataset. Initially the project would have used two mesoscale models, the Mesoscale Atmospheric Simulation System (MASS) and Weather Research and Forecasting (WRF) model, however the main runs only used the MASS method [5].

3.2 Simultaneous optimal bidding in two energy markets

This portion of the investigation focuses on the tertiary reserve service, which may also be known as balance service. It is used to correct energy imbalances during each operating hour of contracted power exchanges. Deviations from planned production result in penalized energy prices rendering less-than-expected revenues for power producers. Errors in forecast are reflected directly in revenues due to these deviations of contractual energy delivery. A larger error in forecast does not necessarily mean a larger revenue penalty because it depends on whether the error is favorable for the system or not. In Sweden, for example, more-than-contracted energy output may be favorable when the system requires up regulation and will not be penalized as severely as when the system requires down regulation. A bidding algorithm proposed by [33] creates the possibility of hedging revenue loss by also participating in the reserve market. It is assumed, however, that down regulation prices are low with wind power participation because this provision has no cost and is always available and is thus considered negligible. Up regulation depends on the availability of wind and so the price for up regulation is expected to be higher. Therefore, only up regulation service is be considered as useful revenue.

3.2.1 Revenue and market design for wind producers theory

The total revenue constitutes the sum from both markets at each hour, represented by equation 3.10. Using the same notation as [33], R_E is revenue from the regular energy market and R_{UR} is the revenue from up regulation. π is the price, P_c is committed power, and T is the additional revenue (positive or negative) from deviation, each for the respective market. These relationships are summarized below:

$$R = R_E + R_{UR} \quad (3.10)$$

$$R_E = \pi_E P_{cE} + T_E \quad (3.11)$$

$$R_{UR} = \pi_{UR} P_{cUR} + T_{UR} \quad (3.12)$$

$$R = \underbrace{\pi_E P_{cE} + T_E}_{R_E} + \underbrace{\pi_{UR} P_{cUR} + T_{UR}}_{R_{UR}} \quad (3.13)$$

The price of energy when it deviates from contract is different for when an energy provider over generates or under generates. The additional revenue, then, depends on the level of output at the hour of operation and the respective price level. Equation 3.14 depicts revenues during these two conditions where π_{E+}, π_{E-} are the price of energy for over and under generation and P_t is the actual power production at that operating hour:

$$T_E = \begin{cases} \pi_{E+}(P_t - P_{cE}), & P_E \geq P_{cE} \\ \pi_{E-}(P_t - P_{cE}), & P_E < P_{cE} \end{cases} \quad (3.14)$$

This optimization assumes that up regulation prices are lower than energy prices, and the price of under provision of either is higher than the respective base price. Additionally, it is assumed that for wind energy, the electricity market is designed in such a way that it fulfills the third price relationship. These assumptions are shown below:

$$0 \leq \pi_{UR+} \leq \pi_{UR} \leq \pi_{UR-} \quad (3.15)$$

$$0 \leq \pi_{E+} \leq \pi_E \leq \pi_{E-} \quad (3.16)$$

$$0 \leq \pi_{UR+} \leq \pi_{E+} \leq \pi_{UR-} \leq \pi_{E-} \quad (3.17)$$

Equation 3.17 determines the priorities of how wind energy is sold. A wind plant that cannot fulfill all commitments ($P_{cE} + P_{cUR}$) tries to fulfill the highest marginal price, π_{E-} , energy. Once it can fulfill this commitment but not able to manage the full commitments, it provides for the next largest marginal price, π_{UR-} . When the wind farm fulfills all commitments and has power to spare, as can be deduced, the generator sells the next service, energy, which is now an over provision of energy, π_{E+} .

3.2.2 Optimized bidding methodology

The optimization of revenue is a maximization problem of the expected revenue by bidding in both markets. Certain restrictions, or contingencies, must apply in order to represent real conditions. Committed power may not exceed total installed capacity. $P_{t\max}$ is the installed capacity of the wind farm. The complete solution may be found in [33].

$$\begin{aligned} \max \quad & E[R(P_{cE}, P_{cUR})] \\ \text{s.t.} \quad & P_{t\max} - P_{cE} - P_{cUR} \geq 0 \\ & P_{cE} \geq 0, P_{cUR} \geq 0 \end{aligned} \quad (3.18)$$

The algorithm needs to define two parameters, A and B , to establish bidding quantities. These A and B parameters depend solely on price signals from the market. A and B may be referred to as bidding quantiles.

$$A = \frac{\pi_E - \pi_{UR}}{\pi_{E-} - \pi_{UR-}}, \quad B = \frac{\pi_{UR} - \pi_{E+}}{\pi_{UR-} - \pi_{E+}} \quad (3.19)$$

As per reference [33], these A and B parameters will determine which bidding strategy to use and the appropriate quantity to bid. Here $F(P_t)$ is the cumulative distribution function of $f(P_t)$, therefore $F^{-1}(1) = P_{t\max}$, the installed capacity.

Case 1

$0 < A < B$ ◦ Bidding in both markets.

$$P_{cE} = F^{-1}(A), \quad P_{cUR} = F^{-1}(B) - P_{cE} \quad (3.20)$$

Case 2

$A > 0, A \geq B$ ◦ Bidding in energy market.

$$P_{cE} = F^{-1} \frac{\pi_E - \pi_{E+}}{\pi_{E-} - \pi_{E+}}, \quad P_{cUR} = 0 \quad (3.21)$$

Case 3

$A \leq 0$ ◦ Bidding in reserve market.

$$P_{cE} = 0, \quad P_{cUR} = F^{-1}(B) \quad (3.22)$$

This method for obtaining bid quantities requires A and B to fall within $[0, 1]$ in order for the evaluations to be valid since they are inverse cumulative distribution functions. In some cases these parameters fall outside the permitted range and the algorithm simply bids in the energy market only with the point forecast.

Note that if price assumption in equation 3.15 is fulfilled then $B \leq 1$, an important limitation of a normalized CDF (beta or normal).

Texas market

The forecast and observation data used for this study is taken from National Renewable Energy Laboratory's (NREL) *updated* Eastern Wind Integration and Transmission Study (EWITS) dataset. The 2006 year data for simulated wind farm site # 0195 is used to generate the forecast probabilities. Prices for energy and reserve capacity are both day-ahead prices from ERCOT nodal market. The same price signals are used in order to compare probabilistic forecasting performance.

Swedish market

The discussed bidding algorithm is applied to the Swedish market for balancing power. The available market data is used from Nordpoolspot's website, showing prices, system status and regulation volumes for every hour. Data for price area S3 is used from the year 2013. However, not all market data is available since the prices are published according to system state. During up-regulation hours, only energy and up-regulation prices are available. Similarly during down-regulation hours, only energy and down-regulation prices are available. For most hours without up- or down-regulation, all prices are the same as the energy price.

4. Application of Methodology and Results

4.1 Stochastic uncertainty estimation

Quantile curves are generated using the three methods described earlier in sections 3.1.2 and 3.1.3 in order to visualize the *pdf* over the wind farm's capacity. Quantiles for *normal* and *beta* distributions over the normalized power range are generated by using the inverse cdf function of the given distribution $q(x) = F_n^{-1}(Q, \mu, \sigma)$ from equation 3.3 and $q(x) = F^{-1}(Q, \alpha, \beta)$ from equation 3.7 where Q is the desired quantile. The quantile ranges used are 5%, 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90% and 95% which are plotted over all forecast data points in figure 4.1.

Using the curves, one can get a picture of how wide the probability window is for any point forecast and how each generally concurs with density of the data points. Observe that near zero the data of the point forecasts is very close together and the quantile curves show that the probability does not vary so much compared to 0.50 where the data points are more sparse.

Figure 4.1 shows both *pdf* methods side by side. Both agree with the variance trend along the wind farm's normalized power capacity range, however the beta *pdf* reaches a maximum before reaching maximum power, trending on almost zero variance. Although a portion after this point of the beta method is truncated and mended with a different method, it is still used in this thesis as a benchmark due to previous works [33].

The quantile regression method is used to generate the quantile curves in figure 4.2. Figure 4.2(a) shows quantile regression fits of the 1st order which

Figure 4.1. PDF quantiles: 0.05, 0.10, 0.20 ... 0.90, 0.95

are essentially straight lines. Visually one can appreciate how poorly these quantiles follow the plotted points. Figures 4.2(b) and 4.2(c) show quantiles of increasing orders with seemingly improved results. The remaining figures 4.2(d) , 4.2(e) , and 4.2(f) are only shown for comparison and not used in the rest of the investigation. One reason is the exponentially increased computing resources required and the other reason being that polynomial quantile fits begin overlapping or intersecting.

4.2 Simultaneous optimal bidding in two energy markets

The discussed bidding algorithm is applied to two markets using the simulated wind power forecasting methods to compare its effect on revenue. The wind power forecast methods are compared to each other in one market. It is assumed the wind farm does not down regulate and does not use any kind of power-limiting, so it generates at full capacity with all available wind.

4.2.1 Bidding algorithm in Texas market

The forecast and observation data taken from NREL's *updated* EWITS dataset is used to generate the forecast probabilities. Quantiles for *normal* and *beta* distributions over the normalized power range are respectively generated by using the inverse cdf function of the given distribution $q(x) = F_n^{-1}(Q, \mu, \sigma)$ from equation 3.3 and $q(x) = F^{-1}(Q, \alpha, \beta)$ where Q is the desired quantile. Penalties for under- and over-provision of energy in both markets are identical to [33] where $\pi_{E+} = 0.1\pi_E$; $\pi_{E-} = 1.9\pi_E$; $\pi_{UR+} = 0.1\pi_{UR}$; $\pi_{UR-} = 1.3\pi_{UR}$. Prices for energy and reserve capacity are both day-ahead prices from ERCOT nodal market. The same price signals are used in order to compare probabilistic forecasting performance.

Table 4.1 shows how the various forecasting methods affects the performance of the bidding algorithm. It may be observed that the performance of the algorithm improves with increasing improvement of the quantile fitting. The hybrid beta-normal *pdf* model for quantile generation performs worse than using the only the normal *pdf* but still renders greater revenue than only placing bids on energy. It is therefore expected that using more advanced real-time forecasting techniques would allow for implementing the bidding algorithm in daily transactions.

4.2.2 Bidding algorithm in Swedish market

Next, the discussed bidding algorithm is applied to the Swedish market for balancing power. The available market data is used from Nordpoolspot's website,

Figure 4.2. Quantile regression quantiles: 0.05, 0.10, 0.20 ... 0.90, 0.95

(a) 1st order

(b) 2nd order

(c) 3rd order

(d) 4th order

(e) 5th order

(f) 6th order

Table 4.1. *Effects of different quantile generation methods with advanced bidding method on wind farm revenue*

Method	Revenue	RMSE of P_{CE} QR-vs-norm
E_{only}	81237520.4536	
Hybrid <i>pdf</i>	81889888.2716	44.092132893
Normal <i>pdf</i>	82009344.2733	(baseline)
QR 1 st order	81991485.2249	11.839415742
QR 2 nd order	82248204.9290	13.953937516
QR 3 rd order	83082846.9093	35.257803607

showing prices, system status and regulation volumes for every hour. Data for price area S3 is used from the year 2013. However, not all market data is available since the prices are published according to system state. During up-regulation hours, only energy and up-regulation prices are available. Similarly during down-regulation hours, only energy and down-regulation prices are available. For most hours without up- or down-regulation, all prices are the same as the energy price. Since this study does not apply a price predicting method and uses historical prices as if they were perfectly predicted, only up-regulation hours are used for this section. The entire year is not simulated because of the nature of the market's available data since prices for up-regulation are only shown during up-regulation system conditions. Up-regulation prices are higher than hourly energy prices and a parametric study is done to compare the effects of the ratio of up-regulation to energy price on revenue and energy commitment using the normal *pdf* for probabilistic forecast.

Reference Scenario

The reference scenario for revenue uses the point forecast to bid in the day-ahead energy market only, applying Swedish market rules and penalties. Under-production of committed power is penalized by paying up-regulation price for the power another producer provides. Over-production of committed power results in payment at market price, no special rewards for providing more unplanned power in up-regulation state. This scenario also provides a reference for how much power is not delivered, when real output is below the forecast. With Swedish market rules, over-production of wind power is sold at a lower market price and does not have additional fuel cost so it represents mostly direct profit if maintenance is omitted. Liang's market rules are similar in this respect.

Tested Scenarios

A range of price ratios between up-regulation and regular energy prices are observed to show how this affects the revenues using the probabilistic bidding method. The first (blue) curve of figure 4.3 (a) represents revenue using

Figure 4.3. Revenue curves for total revenue vs up regulation to spot price ratio

Liang's bidding method and proposed market rules, while the second (green) curve represents Liang's bidding method using today's Swedish market rules and prices. The blue curve in (a) shows much lower revenue due to the more severe penalties for under-generation with Liang's proposed market. In Swedish market, the balance provider who does not provide the balance would pay the difference for another producer to provide up-regulation. However, it is assumed that the wind power producer is a small market player and does not affect the marginal cost of providing additional power so the penalty is practically omitted. In up-regulation system state, under-production is penalized but over-production is paid at regular energy market price.

The curves in figure 4.3 (b) show the change in commitment in both markets as the price signals change. Towards the left, When up-regulation price is practically null, commitments to up-regulation are minimal because there is no benefit in selling this energy to said market. As the price for up-regulation increases, the commitments shift from the regular day-ahead energy market

Figure 4.4. Commitment curves.

to the up-regulation market. However, when the up-regulation price surpasses the spot price for energy, the algorithm only bids in regulation.

As the ratio changes, the A and B variables that determine the quantiles for which market to bid also change. This changes the amount of energy bid in each market. If more energy is committed then there is a greater chance of committing more than is actually produced since the algorithm risks more energy. This means more power is not delivered when the real observed power is deficient compared to the amount that was bid. In figure 4.4, a curve for the undelivered power with the two-market bidding scheme is compared to the undelivered power using the point forecast (bidding the same way in every case). It is observed that undelivered power increases with increasing prices, since more power is risked proportionally to the forecast. Revenue does not decrease due to penalties for under provision. This is based on the assumption that the wind power producer does not have any effects on market prices. Therefore, since the provider only needs to pay the difference of the next provider's energy and the market prices don't change, the difference is zero and is perceived as without penalty for Sweden.

5. Discussion and Analysis

This algorithm was initially designed for a market where up-regulation prices are lower than regular energy and where penalties are high, especially for over-production. Penalties for over production are null in the Swedish observed scenario. This investigation only observes how a small wind farm behaves in up-regulation hours due to the lack of prices for down-regulation or zero imbalance hours. It is assumed that the wind power producer is small enough not to change market price. This assumption results in no penalty for under-generation. This may be applied as a differentiated penalty and serve as an incentive for larger scale participation in the up-regulation market. Nonetheless, in this scenario where the penalty for not delivering up-regulation is minimal and the price is higher than the regular day-ahead market, it is profitable to participate in up-regulation market and not in the energy market.

The thesis reviews one electricity market scheme for two electricity markets supporting the system's need for frequency control in order to complement fluctuations in customer demand. We find that United States and Sweden have similar technical methods for frequency control where local frequency control is activated within a tight frequency range and a centralized control is activated when the system goes beyond this range. The market operates similarly where ancillary providers place bids before delivering the services.

An advanced bidding scheme is simulated by generating forecast quantiles with different methods. The variance from the quad-fit may result in invalid parameter evaluations for predictions when approaching the upper limit; for the dataset used in this investigation it begins around $\mu = 0.94$. To remedy this obstacle, the normal distribution is used with normalized data when estimated beta parameters are invalid, resulting in a hybrid distribution algorithm. This allows for the bidding scheme to complete the iteration for every time step. Different quantile generation methods provide variable amounts of revenue with the bidding scheme, attributed to the precision of the fit to the historical data.

6. Conclusions

This bidding algorithm, with the current objective function and price constraints, is limited in combined bidding of energy and ancillary service in the Swedish market. The parametric study reveals that as long as up-regulation prices are below day-ahead energy, the algorithm will bid in both markets to optimize revenue. When regulation prices are higher than day-ahead then it only bids energy in the regulation market with the current objective function. This algorithm needs to have a more generic objective function and constraints for Swedish market conditions due to ancillary service prices that are higher than scheduled energy. In order to use a joint bidding algorithm in the Swedish market, it must be optimized for these specific market conditions, or a broader algorithm may be designed with inputs that describe the market behaviors to tweak its performance according to these.

Appendices

Parametric sensitivity study for wind power trading through stochastic reserve and energy market optimization

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Abstract—Trading optimal wind power in energy and regulation market offers possibilities for increasing revenues as well as impacting security of the system in a positive way [1]. The bidding in both energy and regulation markets can be computed through stochastic optimization process of both markets as demonstrated in the following paper [1].

Based on this optimization, the impact of price ratios between energy and reserve market is investigated in this study to analyse the impact of price ratios on the revenues for Swedish market.

The parametric study reveals that as long as up-regulation prices are below day-ahead energy, the algorithm will bid in both markets to optimize revenue. When regulation prices are higher than day-ahead then it only bids energy in the regulation market with the current objective function.

I. INTRODUCTION

Increasing amounts of wind power penetration in electrical grids makes research in wind power forecasting all more valuable. Although larger participation of wind energy can reduce overall emissions [3], it calls for more precise wind power predictions in order to minimize impacts on grid stability, security, optimal power flow calculations and unit commitment scheduling operational costs. The cost impact of forecast errors have been found to be largest in the day-ahead scheduling as compared to regulation time-frame [2].

In this study, we will give a short summary of stochastic estimation methods. Probabilistic forecasts of wind energy generation are of high financial importance for wind power industry players to assess the financial risk. Such forecasts can be based on forecast ensembles from numerical weather prediction models which is discussed shortly in the next subsection [6] [7] [8] [9] [10] Probabilistic forecast methods can use ensembles to define the probability of the weather or atmosphere. Ensembles are different possible states in the atmosphere at a certain time. Once ensembles are generated through ensemble forecast system, it is possible to address the risk via quantiles by post-processing ensemble data. In this

study, we will concentrate on the post-processing of ensembles impact on the stochastic optimization of both reserve and energy market for power system[1]. Generation of quantiles needed for stochastic optimization used herein for market optimization will be investigated through deterministic forecast data preliminary. This is to make our comparison consistent with the previous work in literature [1]. The ensembles forecasts discussed in the next subsection will be more statistically and physically complete way of using available information through usage of observations and weather forecast models [6] [7] [8] [9] [10] and this approach has not been pursued since this is beyond the scope of this work.

II. GENERATION OF QUANTILES THROUGH ENSEMBLE OF FORECASTS

The majority of tools provide point forecasts which are given as only one measurement of the predicted power output. A more useful result is a probability forecast which quantifies the uncertainties of the predictions of the regional context. Probabilistic wind forecasts are often based on ensemble prediction systems that can use micro scale or mesoscale weather forecast models. [6][7][8][9]. Numerical weather prediction (NWP) models are run with different initial conditions or different physical models to generate the uncertainty in the forecast to improve predictions. The ensemble forecast algorithms are of special interest due to their simplicity of implementations to other applications where adjoint operators are required. Their potential for efficient use on parallel computers with large-scale geophysical models is another advantage.

The ensembles that are generated through ensemble methods will need to be post-processed afterwards in order to make use of all information available in an ensemble forecast. Ensembles consist of several deterministic forecasts. However as it is the case in this work as discussed in the subsection, it is possible to generate approximate ensembles through single deterministic forecast. It is also possible to create ensembles by use of the variance margin of a single deterministic

Figure 1. VARIANCE - Observed production and its variance plotted to the forecasted power. All the variables are normalized to installed capacity. Perfect prediction would render a 1:1 ratio and therefore a perfectly diagonal line.

forecast in the employed time series as used in the paper[1] [11]. One commercial tool, for example, called Wind Power Prediction Tool (WPPT) uses three methods for uncertainty estimations through Adaptive variance estimation, ensemble based quantiles, and quantile regression[12].

III. GENERATION OF QUANTILES THROUGH SINGLE DETERMINISTIC FORECAST

In this study, single deterministic or point forecast variance margin of the employed time series will be used to generate the time series [1]. Several post processing techniques through definition of parametric distributions or quantile regression exist for ensembles based on quantiles that are generated through this approach. Ensembles may be jointly described with a probability distribution function that is well-known and easily parametrized.

A. Generation of quantiles from point forecast with parametric distributions

To generate probability quantiles from the available time series, one investigated approach is the one employed by [1] used by calculating variance for various power classes, as explained in [11]. Variance of a dataset is defined as:

$$\text{Var}(X) = E[(X - \mu)^2] \quad (1)$$

The variance for every 0.05 step in the normalized power range constitutes one variance value for the mean power in that bracket. As can be seen in figure 1 This means that for a range $(0, 0.05)$, the variance of this range is represented at $\frac{0+0.05}{2} = 0.025$ normalized power, and for the $(0.05, 0.1)$ range, the variance is represented at $\frac{0.05+0.1}{2} = 0.075$. Figure 1 shows the calculated variance plotted across the power

range. Variance is a non-negative value, therefore the resulting quadratic fit cannot give negative values. A contingency for variance as variance σ being y and $y \geq 0$ is set for the fitting since variance may have a zero value, indicating no variance; all values at that point are equal. The figure also shows the resulting fit.

The variance from the quad-fit may result in invalid parameter evaluations for predictions when approaching the upper limit; for the dataset used in this investigation it begins around $\mu = 0.94$. To remedy this obstacle, the normal distribution is used with normalized data when estimated beta parameters are invalid, resulting in a hybrid distribution algorithm. Part of the normal probability density falls beyond the bounds of the beta function $(\beta(x), x \in [0, 1])$ and the valid portion is hence normalized.

IV. SIMULTANEOUS OPTIMAL BIDDING IN TWO ENERGY MARKETS

This portion of the investigation focuses on the tertiary reserve service, which may also be known as balance service. It is used to correct energy imbalances during each operating hour of contracted power exchanges. Deviations from planned production result in penalized energy prices rendering less-than-expected revenues. Errors in forecast are reflected directly in revenues due to these deviations of contractual energy delivery. A larger error in forecast does not necessarily mean a larger revenue penalty because it depends on whether the error is favorable for the system or not. In Sweden, for example, more-than-contracted energy output may be favorable when the system requires up regulation and will not be penalized as severely as when the system requires down regulation. A bidding algorithm proposed by [1] creates the possibility of hedging revenue loss by also participating in the reserve market. It is assumed, however, that down regulation prices are low with wind power participation because this provision has no cost and is always available and is thus considered negligible. Up regulation depends on the availability of wind and so the price for up regulation is expected to be higher. Therefore, only up regulation service is considered as useful revenue.

V. REVENUE AND MARKET DESIGN FOR WIND PRODUCERS

The total revenue constitutes the sum from both markets at each hour, represented by equation 2. Using the same notation as [1], R_E is revenue from the regular energy market and R_{UR} is the revenue from up regulation. π is the price, P_c is committed power, and T is the additional revenue (positive or negative) from deviation, each for the respective market. These relationships are summarized below:

$$R = R_E + R_{UR} \quad (2)$$

$$R_E = \pi_E P_{c,E} + T_E \quad (3)$$

$$R_{UR} = \pi_{UR} P_{c,UR} + T_{UR} \quad (4)$$

$$R = \underbrace{\pi_E P_{c,E} + T_E}_{R_E} + \underbrace{\pi_{UR} P_{c,UR} + T_{UR}}_{R_{UR}} \quad (5)$$

The price of energy when it deviates from contract is different for when an energy provider over generates or under generates. The additional revenue, then, depends on the level of output at the hour of operation and the respective price level. Equation 6 depicts revenues during these two conditions where π_{E+}, π_{E-} are the price of energy for over and under generation and P_i is the actual power production at that operating hour:

$$T_E = \begin{cases} \pi_{E+}(P_i - P_{CE}), & P_i \geq P_{CE} \\ \pi_{E-}(P_i - P_{CE}), & P_i < P_{CE} \end{cases} \quad (6)$$

This optimization assumes that up regulation prices are lower than energy prices, and the price of under provision of either is higher than the respective base price. Additionally, it is assumed that for wind energy, the electricity market is designed in such a way that it fulfills the third price relationship. These assumptions are shown below:

$$0 \leq \pi_{UR+} \leq \pi_{UR} \leq \pi_{UR-} \quad (7)$$

$$0 \leq \pi_{E+} \leq \pi_E \leq \pi_{E-} \quad (8)$$

$$0 \leq \pi_{UR+} \leq \pi_{E+} \leq \pi_{UR-} \leq \pi_{E-} \quad (9)$$

Equation 9 determines the priorities of how wind energy is sold. A wind plant that cannot fulfill all commitments ($P_{E+} + P_{UR}$) tries to fulfill the highest marginal price, π_{E+} , energy. Once it can fulfill this commitment but not able to manage the full commitments, it provides for the next largest marginal price, π_{UR-} . When the wind farm fulfills all commitments and has power to spare, as can be deduced, the generator sells the next service, energy, which is now an over provision of energy, π_{E+} .

VI. OPTIMIZED BIDDING METHOD

The optimization of revenue is a maximization problem of the expected revenue by bidding in both markets. Certain restrictions, or contingencies, must apply in order to represent real conditions. Committed power may not exceed total installed capacity. $P_{\max}$ is the installed capacity of the wind farm. The complete solution may be found in [1].

$$\begin{aligned} \max \quad & E[R(P_{CE}, P_{CUR})] \\ \text{s.t.} \quad & P_{\max} - P_{CE} - P_{CUR} \geq 0 \\ & P_{CE} \geq 0, P_{CUR} \geq 0 \end{aligned} \quad (10)$$

The algorithm needs to define two parameters, A and B, to establish bidding quantities. These A and B parameters depend solely on price signals from the market. A and B may be referred to as bidding quantiles.

$$A = \frac{\pi_{E-} - \pi_{UR-}}{\pi_{E-} - \pi_{UR-}}, \quad B = \frac{\pi_{UR-} - \pi_{E+}}{\pi_{UR-} - \pi_{E+}} \quad (11)$$

As per [1], these A and B parameters will determine which bidding strategy to use and the appropriate quantity to bid. Here $F(P_i)$ is the cumulative distribution function of $f(P_i)$, therefore $F^{-1}(1) = P_{\max}$, the installed capacity.

Case 1: $0 < A < B$ Bidding in both markets.

$$P_{CE} = F^{-1}(A), \quad P_{CUR} = F^{-1}(B) - P_{CE} \quad (12)$$

Case 2: $A > 0, A \geq B$ Bidding in energy market.

$$P_{CE} = F^{-1} \frac{\pi_{E-} - \pi_{E+}}{\pi_{E-} - \pi_{E+}}, \quad P_{CUR} = 0 \quad (13)$$

Case 3: $A \leq 0$ Bidding in reserve market.

$$P_{CE} = 0, \quad P_{CUR} = F^{-1}(B) \quad (14)$$

This method for obtaining bid quantities requires A and B to fall within $[0, 1]$ in order for the evaluations to be valid since they are inverse cumulative distribution functions. In some cases these parameters fall outside the permitted range and the algorithm simply bids in the energy market only with the point forecast.

Note that if price assumption in equation 7 is fulfilled then $B \leq 1$, an important limitation of a normalized CDF (beta or normal).

VII. RESULTS

The discussed bidding algorithm is applied to Swedish market using simulated wind power forecasting methods to observe its effect on revenue. It is assumed the wind farm does not down regulate and does not use any kind of power-limiting, so it generates at full capacity with all available wind.

A. Bidding algorithm in Swedish market

The discussed bidding algorithm is applied to the Swedish market for balancing power. The available market data is used from Nordpoolspot's website, showing prices, system status and regulation volumes for every hour. Data for price area S3 is used from the year 2013. However, not all market data is available since the prices are published according to system state. During up-regulation hours, only energy and up-regulation prices are available. Similarly during down-regulation hours, only energy and down-regulation prices are available. For most hours without up- or down-regulation, all prices are the same as the energy price. Only up-regulation hours are used for this section since this study does not apply a price predicting method and uses historical prices as if they were perfectly predicted. The entire year is not simulated because of the nature of the market's available data since prices for up-regulation are only shown during up-regulation system conditions. Up-regulation prices are higher than hourly energy prices and a parametric study is done to compare the effects of the ratio of up-regulation to energy price on revenue and energy commitment using the normal *pdf* for probabilistic forecast.

1) *Reference Scenario*: The reference scenario for revenue uses the point forecast to bid in the day-ahead energy market only, applying Swedish market rules and penalties. Under-production of committed power is penalized by paying up-regulation price for the power another producer provides. Over-production of committed power results in payment at market price, no special rewards for providing more unplanned power in up-regulation state. This scenario also provides a reference for how much power is not delivered, when real output is below the forecast. With Swedish market rules, over-production of wind power is sold at a lower market price

Figure 2. Revenue curves for total revenue vs up regulation to spot price ratio

and does not have additional fuel cost so it represents mostly direct profit if maintenance is omitted. Liang's market rules are similar in this respect.

2) *Tested Scenarios*: A range of price ratios between up-regulation and regular energy prices are observed to show how this affects the revenues using the probabilistic bidding method. The first (blue) curve of figure 2 (a) represents revenue using Liang's bidding method and proposed market rules, while the second (green) curve represents Liang's bidding method using today's Swedish market rules and prices. The blue curve in (a) shows much lower revenue due to the more severe penalties for under-generation with Liang's proposed market. In Swedish market, the balance provider who does not provide the balance would pay the difference for another producer to provide up-regulation. However, it is assumed that the wind power producer is a small market player and does not affect the marginal cost of providing additional power so the penalty is practically omitted. In up-regulation system state, under-production is penalized but over-production is paid at regular energy market price.

The curves in figure 2 (b) show the change in commitment in both markets as the price signals change. Towards the left, When up-regulation price is practically null, commitments to up-regulation are minimal because there is no benefit in selling this energy. As the price for up-regulation increases, the commitments shift from the regular day-ahead energy market

Figure 3. Commitment curves.

to the up-regulation market. However, when the up-regulation price surpasses the spot price for energy, the algorithm only bids in regulation.

As the ratio changes, the A and B variables that determine the quantiles for which market to bid also change. This changes the amount of energy bid in each market. If more energy is committed then there is a greater chance of committing more than is actually produced since the algorithm risks more energy. This means more power is not delivered when the real observed power skews below the amount that was bid. In figure 3 a curve for the undelivered power with the two-market bidding scheme is compared to the undelivered power using the point forecast (bidding the same way in every case). It is observed that undelivered power increases with increasing prices, since more power is risked proportionally to the forecast. However, revenue does not decrease due to penalties for under provision because of the assumption that the wind power producer does not have any effects on market prices. Therefore, since the provider only needs to pay the difference of the next provider's energy and the market prices don't change, the difference is zero and is perceived as without penalty for Sweden.

B. Conclusions

This algorithm was initially designed for a market where up-regulation prices are lower than regular energy and penalties are high, especially for over-production which are null in the Swedish observed scenario. Nonetheless, in this scenario where the penalty for not delivering up-regulation is minimal and the price is higher than the regular day-ahead market, it is profitable to participate in up-regulation market and not in the energy market. However, this investigation only observes how a small wind farm behaves in up-regulation hours due to the lack of prices for down-regulation or zero imbalance hours. The assumption that the wind power producer is small enough not to change market price results in no penalty for under-generation. This may be applied as a differentiated penalty and serve as an incentive for larger scale participation in the up-regulation market.

This bidding algorithm, with the current objective function and price constraints, is limited in combined bidding of energy

and ancillary service in the Swedish market. The parametric study reveals that as long as up-regulation prices are below day-ahead energy, the algorithm will bid in both markets to optimize revenue. When regulation prices are higher than day-ahead then it only bids energy in the regulation market with the current objective function. This algorithm needs to have a more generic objective function and constraints for Swedish market conditions due to ancillary service prices that are higher than scheduled energy. In order to use a joint bidding algorithm in the Swedish market, it must be optimized for these specific market conditions, or a broader algorithm may be designed with inputs that describe the market behaviors to tweak its performance according to these.

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