MASTER

Verification methods for delivery of ancillary services provided by wind assets

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Verification methods for delivery of ancillary services provided by wind assets

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Executive summary

Due to the changing energy landscape in which more and more electricity is produced by renewable electricity sources, a rising demand for Ancillary Services (AS) is expected. As the conventional providers of AS capacity get phased out, renewable energy producers like solar and wind need to take over the supply of these services. Related to the intermittent, variable and weather dependent output of renewables, the existing methods to correctly verify the delivery of actioned AS capacity cannot be applied for these assets. Transmission System Operators (TSOs) are now exploring how to update these methods in order to allow future participation of alternative AS capacity. As wind energy is the main source of renewable generation in The Netherlands, this research is focussed on getting more insight into how to improve verification concerning AS delivered by wind asset. Examining such a method also raises the question how that method does affects the diffusion of alternative supply of wind power as an AS. Therewith, this research contributes to the innovation sciences in outlining which strategic aspects are important to further stimulate the diffusion of the alternative supply methods for AS. The research focusses on answering the following main research question:

"To what extent can verification methods be updated in order to improve verification concerning ancillary services delivered by wind asset?"

In order to improve verification methods of AS, a thorough understanding of how AS function is required. The first chapter explains what AS are and what role they play in maintaining the integrity and stability of the electricity system. Two main categories of AS are examined; congestion management and balancing services. All individual markets related to these two main categories are explained. The related contracting method, bidding process, method of activation, financial settlement and other specifications of the different AS are defined. Thereafter in the next chapter, the relevance of verifying the delivery of ancillary services is discussed. For each of the individual products it describes whether or not there is a verification process. For the balancing products, the current methods are explained. However, no verification occurs for the redispatch products. While the total costs for redispatch increases and the assets delivering redispatch capacity get smaller and more distributed, the relevance of verifying whether the actioned redispatch was actually delivered on the right location increases. And so, a need for verification of actioned redispatch was identified. In Chapter 3 the current and future role of wind assets in delivering AS is described. It demonstrates the technical capabilities of wind assets to deliver AS products and discusses the existing available active power (AAP) method which can be used for verification. Although this method seems to be accurate and suitable for verification, it requires setting up new data streams with the wind assets who provide the AS in order to get the Supervisory Control And Data Acquisition (SCADA) data. Collecting all this data from the individual assets incurs transaction costs for both the system operator as the asset owner. Whereas TenneT wants to open up the redispatch market for smaller distributed assets, it wants to keep the barriers to enter the redispatch market low. Moreover, the work and costs it entails for TenneT to collect and process all the data of these individual assets is undesirable.

Examining the current AS markets and processes exposed the need for a verification method for the delivery of redispatch by wind assets. Concerning the large amount of individual wind assets, the method should be able to be automated, be uniform (applicable to different types of wind

turbines) has to use the existing data streams. Taking these design requirements into account, in Chapter 4, the existing AAP methodology which uses SCADA data of the wind turbine as input was transformed to a data-driven AAP methodology using reanalysis data as input. The data-driven approach makes the method uniform and applicable regardless of the type of wind asset. The method simply learns from the relationship between the wind conditions and the generation output of the asset as a whole based on historical data without needing asset specific information. Furthermore, by using a reanalysis as input, only the coordinates of the asset need to be known to determine the historical wind conditions at the location of the asset. The location of an asset is included in the EAN registration of a grid connection and is therefore known by the grid operator. In this way, no new data stream between the grid operator and the asset owner is required in order to exchange the SCADA data of the turbines. Moreover, the method can use the information of the redispatch action together with the observed difference between the calculated AAP and the actual output of the asset to automatically verify if both correspond.

As there was a knowledge gap in the reviewed literature on how an AAP method would perform using meteorological reanalysis as wind input data, the method as decribed above was developed and tested on actual generation output data. The method was tested on five large wind parks in The Netherlands using the historical production data and the Dutch Offshore Wind Atlas (DOWA) reanalysis. Three models were compared, including linear regression, k-nearest neighbors and XGBoost. The performance of the models was then estimated using 10-fold cross validation. For all individual parks the XGBoost algorithm outperformed linear regression and k-nearest neighbors in terms of accuracy. It demonstrated to be able to estimate the output of the parks on an hourly basis reasonably well with an average MAE of 6.87% of the installed capacity over the five parks. When comparing the DOWA reanalysis data as input with the data of an actual weather station as input, the latter showed only to be slightly more accurate. The performance decreased to an average MAE of 8.49% of the installed capacity over the two parks modelled on a 10-minute time interval. Based on the production data of Gemini, the DOWA reanalysis was compared to the ERA5 reanalysis which has the advantage of being available within 5 days of real time. The DOWA reanalysis slightly outperformed the ERA5 reanalysis in terms of accuracy.

At last, the XGBoost algorithm was tested on all 13 actual redispatch actions which occurred within the timespan of the available dataset. In four cases the model identified curtailment very clearly, at four cases the model partly identified curtailment and at five cases the model underestimated the production during the redispatch period. However, the actual redispatch actions were very small shares of the installed capacity, even smaller than the uncertainty of the model (around 2%). It is expected that the method is better in identifying curtailment when larger shares of the installed capacity are actioned.

Withal, the method does not seem to be accurate enough to be used for actual financial settlement as it entails too much uncertainty. Also more research on how the model behaves at smaller assets is required. Nevertheless, the method could still be useful to monitor delivery of hourly blocks of downward capacity for redispatch actions when no access to SCADA data is available. When the model identifies clear cases of non-delivery, this information could be addressed to the asset owner which should be able to explain the situation. This is already an improvement over not having any verification on the actioned redispatch. Overall, it can be concluded that the verification methods for AS delivered by wind assets can be updated by implementing a data-driven modelling approach using a public meteorological reanalysis for verification of actioned redispatch delivered by wind asset.

Abbreviations

AAP	Available Active Power
AC	Alternating Current
aFRR	Automatic Frequency Restoration Reserve
AS	Ancillary Services
ACM	Autoriteit Consument en Markt
BRP	Balancing Responsible Party
BSP	Balancing Service Provider
DOWA	Dutch Offshore Wind Atlas
DSO	Distribution System Operator
ENTSO-E	European Network of Transmission System Operators for Electricity
ETPA	Energy Trading Platform Amsterdam
FCR	Frequency Containment Reserve
FVR	Frequentie Vermogens Regeling
GOPACS	Grid Operators Platform for Congestion Solutions
IDCONS	Intraday Congestion Spreads
ISP	Imbalance Settlement Period
OWEZ	Offshore Windpark Egmond aan Zee
PAWP	Prinses Amalia Wind Park
KNN	K-Nearest Neighbors
kV	Kilovolt
LES	Large Eddy Simulation
LFC	Load Frequency Control
mFRR	Manual Frequency Restoration Reserve
mFRRda	Manual Frequency Restoration Reserve direct activated
mFRRsa	Manual Frequency Restoration Reserve scheduled activated
MW	Megawatt
MAE	Mean Absolute Error
ROD	Reserve Power Other Purposes
RMSE	Root Mean Squared Error
RPG	Reserve Providing Group
RPU	Reserve Providing Unit
SCADA	Supervisory Control And Data Acquisition
TI	Technical Installation
TSO	Transmission System Operator
TSP	Transport Service Provider
vRES	Variable Renewables
XGBoost	Extreme Gradient Boosting

Content

Index of Figures

Index of Tables

Introduction

The increase of renewable energy production during the last few years has been remarkable. Policies directed to limit emissions of greenhouse gasses will most probably assure a stable growth of electricity generation from renewables, or even accelerate this growth. Related to this current (and yet to come) increase of renewable electricity production some operational challenges within the electricity grid will arise. In particular the variable and stochastic producers, like solar and wind, will cause challenges for TSOs related to safekeeping the integrity of the electricity grid.

First of all, because of the unpredictable, stochastic nature of solar and wind, overall forecasting errors are expected to increase and raise the demand for Ancillary Services (AS). Weather dependent renewable energy already bring more variability and limited predictability into to the electricity system (Ortner & Totschnig, 2019). This causes an increase of the usage of Ancillary Services (AS) which are 'all services required by the transmission or distribution system operator to enable them to maintain the integrity and stability of the transmission or distribution system as well as the power quality' (Eurelectric, 2004, p.9). These AS are offers of upward or downward capacity, which are purchased by the system operators through various markets to restore balance or avoid congestion within the system.

Second, the amount of conventional generators which till now have mostly provided AS will decrease. Currently, this capacity is mainly delivered by coal and gas fired power plants (Martin-Martinez et al., 2014). However, as these conventional plants will be phased out, wind, solar, electric cars, battery storage and demand side response will be required to take over this conventional supply of AS. Curtailing the output of wind and solar plants will play an important role in the provision of downward AS capacity. Nonetheless, currently the share of wind and solar in providing this AS capacity is relatively small in the Netherlands. For wind, solar and these other alternative assets, it is already technically feasible to deliver different types of AS, however, financial profitability and/or market design hinders actual presence as AS (Edmunds et al., 2019; Sorknæs, Andersen, Tang, & Strøm, 2013; Cagnano, Torelli, Alfonzetti, & De Tuglie, 2011; Huda, Aziz, & Tokimatsu, 2018; Fernandes, Frías, & Reneses, 2016; Hansen, 2018). The main reason that AS markets are not yet profitable for renewables is that they receive subsidies for each megawatt (MW) they produce. When they offer downward capacity, the price they receive for the downward capacity needs to cover the loss of this subsidy and therewith limiting the moments they can participate. Another reason is that the current market design requires AS providers to guarantee a certain amount of capacity for monthly and weekly periods. As renewables have large variability and limited predictability, they are not able to guarantee capacity for such a long period. However, market design will be adjusted in the near future as capacity will be contracted for daily periods (TenneT, 2018a). Besides, the subsidies are decreasing and the first wind park without subsidy has already been tendered (Rijksoverheid, 2019). Therewith, it gets financially more attractive for renewables to participate in AS markets and the future participation of renewable AS supply methods is expected to increase.

To facilitate this future participation, TenneT, as the Dutch transmission system operator (TSO), is running (pilot) projects to test implementation. However, one of the most important hurdles from a TSO perspective to allow these alternative supply methods as AS providers, is to develop suitable verification methods which verify the proper delivery of the capacity as requested. When there is no proper method which assures that the AS capacity was delivered to the right extent, this could lead to gaming behaviour of market participants. They can in that case sell the same capacity in different markets. As the AS capacity is intended to solve a problem in the electricity grid, non-delivery can aggravate problems. For this reason it is important to have a suitable method which insentivices AS providers to accurately deliver the capacity as requested.

Present verification methods estimate a reference load(or ‘baseline’) for AS providers, which is the load without the delivered AS capacity. This reference load is then compared with actual measurement data of the provider, which can confirm the proper delivery of the requested power by the TSO (Lee et. al. , 2019; TenneT, 2018b; TenneT, 2018c). The reference load for providers with conventional production units is relatively well definable while they are somewhat constant and follow regular patterns. Contrarily, due to the stochastic and intermittent nature of renewable electricity caused by weather dependency, different techniques or methods are required to define a reference load when renewables are involved.

As the Dutch government aims to have 11 GW installed offshore wind capacity by 2030, it is unavoidable that wind energy has to fulfil an important role in AS provisioning in the Netherlands (Rijksoverheid, 2018). As Vandezande et al. (2010) argue: “the presence of wind power in a system increases the need for regulating and reserve power in order to handle its variability and limited predictability. As indicated by various studies, balancing power requirements are expected to increase proportionally with growing wind power penetration” (p. 3146). Therefore, within Dutch electricity system, there will be an increasing need for wind offering capacity for AS in the near future. In order to operate fair congestion and balancing markets and avoid gaming behaviour of AS providers, it is important to have effective verification in place which monitors whether the AS capacity was delivered to the right extend. However, as TSOs still struggle with how to verify the delivery of downward AS capacity it is important to examine how and for which AS markets these methods can be updated in order to allow correct verification. Solving this specific verification problem contributes to innovation sciences in the sense that gives insight in how to keep operating fair AS markets with the participation of new types of AS providers. The research tries to examine the solutions that are suitable but also takes into account which methods allow the further diffusion of renewables within the AS markets. An important aspect is to take into account the barriers of entry the method might raise. Therewith, it is not only a technical problem, but requires strategic decisions about which method would be best to stimulate the alternative supply of wind power as an AS. From this the main research question arises:

“To what extent can verification methods be updated in order to improve verification concerning ancillary services delivered by wind asset?”

At first it is important to understand what role AS play in operating the electricity system. The different AS products and there role in maintaining the stability and integrity of the electricity system will be discussed in the first chapter. In the Netherlands, all AS capacity is purchased through single buyer markets organized by the TSO. This chapter will explain how these different markets function. In order to get insight into the role AS and how their related markets function, the first chapter tries to answer the sub question:

“What are ancillary services and how do the different ancillary services markets function?”

It also important to review the relevance of verification of the delivery of this capacity. Why is it important that the AS capacity which is purchased by the TSO gets delivered correctly. Chapter two will therefore review the relevance of verification as well as summarize which methods are currently used to verify the delivery of AS. This is done using the sub question:

“What is the relevance of verification of correct delivery of actioned AS capacity and what methods are currently used for this?”

Literature regarding delivery of AS with wind will be summarized in chapter three. The technical capabilities of wind turbines to deliver AS capacity will be reviewed. The chapter also discusses what currently hampers the participation of wind assets in AS markets. Furthermore, the existing research focussed on verifying the delivery of downward capacity by wind asset will also be discussed and is centred around the sub question:

“How do wind assets participate in AS markets and which methods are used to verify the delivery of AS capacity delivered by wind assets?”

Evaluating the above sub-questions and the developments within the AS markets, a need for a uniform verification method for wind assets delivering redispatch was identified. The main idea is to develop a model based on historical generation output of the wind asset as a whole, combined with the historical local weather conditions at the location of the wind asset. This model can than estimate the maximal possible production or active available power (AAP) of the wind asset based on the wind conditions during the period that the downward redispatch capacity should be delivered. This estimated AAP can than be used as a baseline or reference values to verify whether the downward capacity was actually delivered.

So far, all decribed methods in literature use the nacelle anemometer wind speed (NWS) from individual wind turbines in the park which are communicated through Supervisory Control And Data Acquisition (SCADA) systems. However, this data is often not easy to acquire or involves setting up new data connections between the wind park operator and the TSO. Especially for smaller assets these type of transaction costs might be too costly and could form a barrier to offer downward AS capacity to the TSO. As verification of the delivery of balancing services is done on a very short time interval (up to 2 seconds), this requires wind input data on this same time scale. SCADA data therefore seems to be unavoidable in order get access to these highly time specific wind conditions. However, redispatch is contracted by hourly or 15-minute blocks, therewith having wind data on these time scales could be sufficient to verify the delivery. Hence, it is relevant to investigate other ways of acquiring these local wind conditions to avoid having to set up new data streams. Meteorological reanalysis is a method which provides a picture of the weather of the past as close to reality as possible. It combines local weather observations (e.g. satellite images or observations of weather stations) with weather models to provide a consistent picture of the past weather at a local level. The quality of these historical weather grids has been improved significantly during the last decades (Boehme and Wallace, 2008). Therefore, publicly available meteorological reanalyses which provide local historical wind conditions on an hourly and for some areas on a 10-minute time scale, could offer a solution for this. However, a knowledge gap was identified in the literature. There is no research to what extend this public meteorological reanalysis data can be used to verify the delivery of downward capacity by wind assets. For that reason, chapter 4,5 and 6 try to fill this knowledge gap by proposing and testing a method using public meteorological reanalysis data. The proposed method will be modelled and tested on the generation output data of five Dutch wind parks. The chapters try to answer the following sub question:

“To what extent is it possible to verify the delivery of downward redispatch by wind assets in a uniform, automated way when using public reanalysis wind data?“

Chapter 1: Ancillary Services Markets

As this research aims at exploring how to update verification methods for the delivery of AS provided by wind assets, it important to get a thorough understanding of how the markets for AS function. AS are a range of capacity products which the TSO contracts to guarantee the system security, it is useful to understand the purpose of all of these products, as well as the relationship with each other. This chapter gives an overview of the most important AS and how their related markets function. It tries to answer the question:

“What are ancillary services and how do the different ancillary services markets function?”

TenneT is the transmission system operator in the Netherlands. They have the responsibility of transporting electrical power on the national level. TenneT is a regulated natural monopoly which has the task of building and maintaining the transmission infrastructure. This includes building and maintaining the physical infrastructure as well as managing the security of the power system in real time. In order to manage the security of the power system TSOs have a set of tools called Ancillary Services(AS). These services include; “black start capability (the ability to restart a grid following a blackout); frequency response (to maintain system frequency with automatic and very fast responses); fast reserve (which can provide additional energy when needed); the provision of reactive power” and redispatch (ENTSOE, 2019, p. 1). As the TSO has a monopoly on operating the grid, it is therefore also the only party contracting these type of services. TenneT procures most of these services in a market based way as prescribed by European regulations (Kooijman, 2018; TenneT, 2019a). In this chapter the procurement of redispatch as a form of congestion management is described. Furthermore, the three most common AS which have been standardized by ENTSO-E namely Frequency Containment Reserve (FCR), automatic Frequency Restoration Reserve (aFRR) and manual Frequency Restoration Reserve (mFRR) are also considered. The reason that these products are considered is the fact that they show a lot of similarities and can technically be delivered by wind assets. In essence it is both procurement of upward or downward capacity with varying time scales and different requirements. The lessons learned within these markets can therefore be translated when regarding a verification method for one specific market.

1.1 Congestion management

Congestion on the electricity grid occurs when the forecasted or the actual power flows pass the thermal limits of the grid elements (Commission Regulation (EU) 2015/1222). Thus, when power flows caused by generation and load are too large to be transferred by the transmission grid (Hirth & Glismann, 2018). As a TSO, TenneT has the responsibility to manage the congestion which arises on the transmission grid (110 kV and up). Whereas the local DSOs are responsible to manage the congestion arising on the distribution grids (below 110 kV). Based on line topology and the distribution of loads, calculations are made by the TSO and DSOs to determine the maximum feasible load flows on the their lines. When the congestion leads to situations where the security of supply is in danger, congestion management measures need to be applied. According to Hirth & Glissmann (2018), the strain on the transmission grid in terms of congestion has increased during the past two decades within the European electricity systems. Building new transmission lines or sub-stations can be measures to reduce congestion on the existing network. However, these type of measures entail years or decades before being realized. To avoid congestion on a short-term timescale, a TSO can apply remedial actions which are; "actions to maintain the operational security as well as to relieve physical congestion on their networks" (EUETS, 2019).These remedial actions can be divided in costly and non-costly actions. Non-costly actions will be the first actions which are employed by a grid operator as they entail measures which do no entail significant costs and are relatively easy to carry out. The most important example of a non-costly action is changing the grid topology, using switch gear, to create different power flows on the network. When these actions alone do not solve the congestion problem, costly actions will be utilized.

In the Netherlands the two main costly remedial actions comprise restriction contracts and redispatch. Restriction contracts are contracts with market parties to supress the production for a defined period of time, the price for this restriction is defined within the contract. For instance when the TSO has a maintenance on a certain line this can cause a congestion as there is less transport capacity available. The TSO can then make a restriction contract with a large market party which uses this line to avoid congestion. However, the most used remedial action for congestion management is redispatch (Tennet, 2019). While restriction contracts limit a market party to a certain production a priori, redispatch manages congestion on D-1 and intraday after market parties have traded on the day-ahead market. Based on the production and consumption prognoses of connection points, so-called T-prognoses, congestion can be forecasted. Flow based models use this T-prognoses as input and identify potential overload on lines and sub-stations. The models identify which areas are congested and where redispatch is required. Subsequently, the TSO requests producers or consumers in the congested areas to reduce their generation or raise their consumption (energy withdraw). While the total balance within the system as a whole may not be disturbed, a counter action is necessary outside of the congested area. To maintain this balance generators or consumers outside of the congested area need to raise generation or reduce consumption to the same extent (energy injection) (Wohland et al., 2018). In the Netherlands, the total costs for congestion management in 2018 were €53 million. These costs include restriction contract costs but are for the largest share related to redispatch costs (Tennet, 2019).

1.1.1 Remedial action process

After closure of the Day-ahead market at D-1 12:00, owners of each individual connection point exceeding 2 MW need to send the expected exchange with the electricity grid for each hour for the next delivery day. This expected exchange is called a Transport prognosis or T-prognosis and should be submitted before 15.15h D-1. Due to the new Generation and Load Data Provision Methodology (GLDPM) regulations, from April 2019 the hourly T-prognosis interval will change to 15 minutes. Besides, in the further future(date is still unknown), the GLDPM requires each connection with a capacity of 1 MW or larger to provide T-prognoses (Enexis, 2019). When parties are connected to the DSO networks they need to send it to the DSO and when parties are directly linked to the transmission grid (≥ 110 kV), they need to send it to the TSO. Although the accountability of delivering the T-prognosis lies with the owner of the connection, in reality the BRPs will send the T-prognosis on behalf of the owners to the DSOs and TSO. The DSO will forecast the transport on their lines for connections below the 2MW threshold and use the received T-prognosis determine the transport on their connection point with the transmission grid.

Consequently, the TSO receives T-prognoses on each substation connecting DSO networks with the transmission gird but has no insight into the transport within the DSO network.

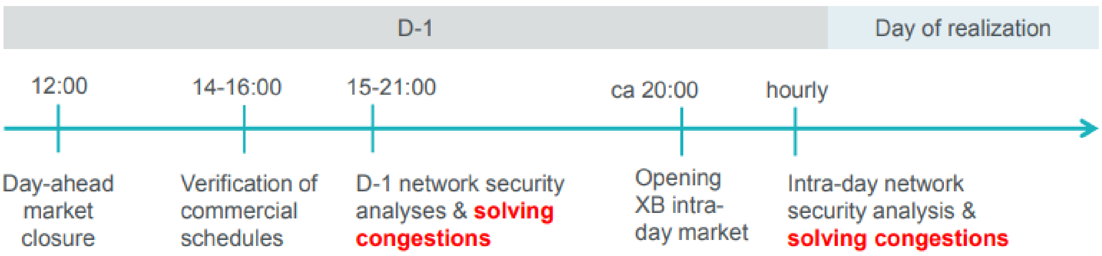

Figure 1: Process of solving a congestion problem

After 15.15h D-1 when TenneT has received all prognoses, they will impute these prognoses into a grid model assessing network security. The model will designate the parts within the system which will experience more transmission than viable, indicating for remedial actions. Nonetheless, after TenneT has made the network security analysis for the Netherlands, they will wait for the analyses results of the other European TSOs. The load flows in network of neighbouring grids can cause extra transport flows within the Netherlands or help relieve congestion on parts of the Dutch grid. For this reason the TSOs share their models to assess the load flows on a European basis. Based on these results TSOs will take remedial actions. As described above, they will first implement non-costly actions like adjustment to line topology before concerning redispatch. But when the non-costly actions are insufficient to retain security of the network, redispatch will be applied. In the Netherlands the redispatch is procured in a market-based way via two different market platforms. The platforms are called GOPACS and Reserve Power Other Purposes (ROD), which will be described in the parts below. All capacity offered via GOPACS will be actioned first and if this does not solve the congestion problem the remaining capacity will be actioned via RESIN (GOPACS, 2019b). If the offered capacity on both market platforms does not sufficient for solving the congestion problem the grid operator can manually contact asset owners to perform redispatch. After the redispatch has been actioned, market restrictions are declared upon the congested area(s). These restrictions bring about that market participants within these area(s) are forbidden to increase their generation and load above the value which was specified in their last T-prognosis before the market restrictions were imposed. Market parties are still permitted to change their generation and load in the opposite direction as it only helps solving the congestion.

1.1.2 GOPACS

Grid Operators Platform for Congestion Solutions (GOPACS) is a newly developed platform in the Netherlands for congestion management. It is a joint collaborations among the DSOs (Stedin, Liander, Enexis and Westland Infra), TenneT and the intraday trading platform ETPA (Energy Trading Platform Amsterdam) (GOPACS, 2019c). The grid operators can activate intraday bids with a specific connection point to solve a congestion problem.

The intraday market works with buy and sell orders, when the price of two of them matches, a trade is made and a specified amount of energy is shifted from the portfolio of one BRP to another BRP. During this continuous process, a lot of intraday orders remain unmatched. In other words, there are parties willing to sell or buy energy but the prices of the buy and sell orders do not match. The GOPACS platform makes use of these remaining unmatched orders by paying the spread between the buy and sell order when the location of both is specified and the combination of orders can solve a congestion problem. These matches are called intraday congestion spreads or IDCONS.

The mechanism is visualized in Figure 2. When there is a congested line, the amount of capacity needs to be reduced on one side of the line and increased on the other side of the line. So, downward redispatch needs to be conducted within one area and upward redispatch need to be conducted within the other area. In this case, a buy order needs to be activated in the downward redispatch area and a sell order in the upward redispatch area. When these buy and sell orders with specified location are available but the price does not match, the algorithm calculates the lowest spread with the remaining unmatched orders. This solution is provided to the TSO or DSO which can then activate the IDCONS. After activation, the intraday platform receives an order pair and clears the order. Subsequently, the spread between the orders is payed by the grid operators in order to solve the congestion. When the TSO or DSO has a need for congestion management, but the matching orders solving this congestion problem are not available, it will send out a market messages specifying the areas in which downward and upward redispatch is requested. In this way it notifies the market parties and encourages them to provide location specific bids within these two areas. Through this system, the grid operators only pay the spread between the orders and the market parties themselves pay the rest. There are no minimum or maximum prices or volumes regarding IDCONS (GOPACS, 2019a).

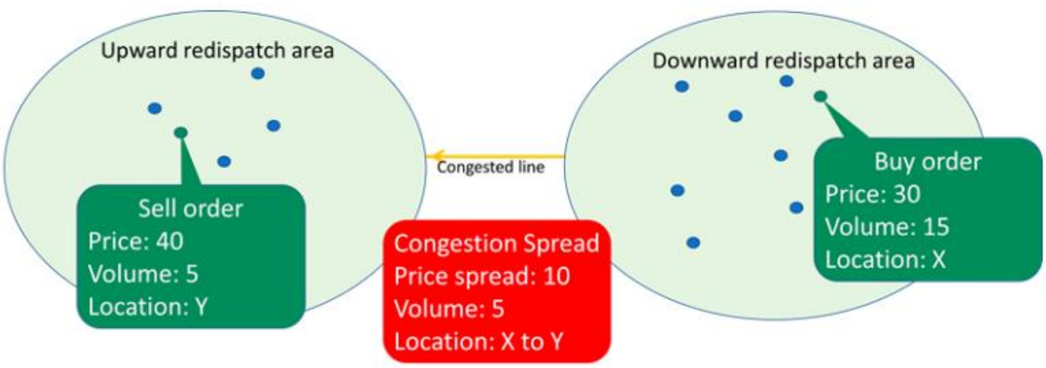

Figure 2: Illustration of a congestion spread (Hirth & Glismann, 2018).

The platform is now experimenting with virtual EAN codes in order to allow a group of assets to be able to offer the redispatch. In this case the market party has own responsibility to prove the correct delivery of the requested energy (GOPACS, 2019a).

The platform was initiated while within the traditionally used product for redispatch, 'reserve for other purposes', there were only a limited amount of traditional market parties participating asking high prices. As of an expected increase in redispatch due to the energy transition, TenneT was searching for a way to increase the amount of redispatch suppliers and to increase the competition (Hirth & Glismann, 2018). The minimum required capacity is also lower which allows access for smaller assets. Besides, the platform also gives the DSOs an instrument to solve congestion within their own networks. The first trails of the platform started in 2017 and from 2019 the platform is used in the daily operations (Hirth & Glismann, 2018). The market party is only allowed to use EAN codes with have a 15 minute allocation, so the energy is measured per 15 minutes.

In order for market parties to start delivering IDCONS, the market party should be connected to the trading platform which supports IDCONS. Which is currently only ETPA but IDCONS should come available on other intraday platforms in the future. Further the market parties should sign an agreement which involves the rules and obligations for participating with the GOPACS platform. They also need to indicate the EAN-codes which will be used for delivering the redispatch capacity. These EAN-codes will be registered by the grid operators and integrated into their systems in order to be integrated as congestion solutions for the system operators. The current design of IDCONS allows that bids can be partially settled relative to the volume. The grid operator is able to use only its required share of the bid. Nonetheless, the chance that this partial settlement will happen in practice is very low as congestion problems often require large capacities to be solved (Renaud, 2019).

Table 1: Summary of the main characteristics regarding GOPACS

Minimum capacity	0.5 MW
Maximum start up time	No start up time is indicated in the bid
Full activation time	No preparation period
Ramp rate	No activation speed is indicated in the bid full activation at indicated ISP
Method of activation	Activation by TSO control room via the intraday market platform ETPA
Product period	Minimum 1 ISP for market party
Acquisition Timing	Acquisition on intraday market
Capacity requirement for the Dutch LFC area	None
Contracting method	Daily messages for congestion
Financial settlement	Compensation for energy supplied or consumed (€/MWh)
Frequency of activation	1x in 2 dagen
Prequalification process	No PQ-test
Delivery location	On EAN-level, possibly on virtual EAN-level
Remuneration	Pay as bid

1.1.3 Reserve Power Other Purposes (ROD)

Reserve Power Other Purposes or Reservevermogen Overige Doeleinden (ROD) is the name of the product TenneT traditionally uses for redispatch. Through ROD, TenneT tries to have enough capacity available to solve congestion problems. ROD is a market based approach for redispatch in which so-called Transport Service Providers (TSP) can offer capacity via bids, voluntary and non-voluntary. If the connection capacity of market participants is 60 MW or more, they are obliged to offer the power which can be generated or consumed less or more than scheduled, to TenneT via bids in ROD. When parties have a connection with less than 60 MW of capacity, they can submit bids voluntary for capacity they have available. The minimum capacity of a bid should always be 1 MW (Product specifications reserve power other purposes, 2019).

The bids can be made within a system called RESIN. The properties which need to be specified when making a bid within RESIN are; the preparation period, the delivery period and the location of the offered capacity. Hence, the TSP can determine the preparation period it needs for delivering the capacity. The preparation period is always at least 3 Imbalance Settlement Periods(ISPs) but can also be more if preferred by the TSP. The minimum delivery period of the bids should always be 4 ISPs or more. The capacity which is offered is always location-specific as it is intended to solve congestion; a location related problem. Therefore the EAN code should be specified when making a bid. The ROD market opens D-7 and from this moment the bids can be submitted to the RESIN platform till D-1 14.45, when the market closes. From 15.00, TenneT can start purchasing the bids to solve congestion problems. In practice they will not yet start purchasing capacity till after the results of the European network security analysis are available. In general TenneT will wait as long as possible before activating bids while circumstances within the grid can change during the day typically 2-3 hours before delivery.

While the network security analysis is based upon the T-prognoses, the activated redispatch volumes are relative compared to the T-prognosis at the time of activation. Therefore the activation must be delivered in addition to the planned dispatch for the specified delivery period. Directly after the ROD bid is activated by TenneT, the TSP should provide an updated T-prognosis to the grid operator which includes the activated ROD capacity. This updated T-prognosis is then again used as input for the network security analysis to assess whether the congestion problem is solved. When the assets deliver redispatch volumes, this creates an imbalance within the BRP portfolio of these assets. Thus, this imbalance is corrected by TenneT for the involved BRP portfolios. The volume which is corrected is the same volume as specified within the bid per ISP (Product specifications reserve power other purposes, 2019). This inclines when a TSP would not deliver the required ROD volume, they will create an imbalance within their BRP portfolio and therefore pay the imbalance price for the volume which was not delivered.

Table 2: Summary of the main characteristics regarding Reserve power other purposes

Minimum capacity	1 MW
Maximum start up time	No start up time is indicated in the bid
Full activation time	Provider can determine its own preparation period. Which is greater or equal to 3 ISPs
Ramp rate	No activation speed is indicated in the bid
Method of activation	Manual activation by TSO via electronic message
Product period	≥ 4 ISPs
Acquisition Timing	Acquisition between D-1 15:00 and 3 ISP's before ISP of delivery
Capacity requirement for the Dutch LFC area	425 MW symmetrical (Q1-2 2019) 385 MW symmetrical (Q3-4 2019)
Contracting method	Daily auctions Consumers or producers which have a total connection capacity exceeding 60 MW are obliged to make bids. Parties with connections below 60 MW can submit voluntary bids.
Financial settlement	Compensation for energy supplied or consumed (€/MWh) pay as bid
Remuneration	Pay-as-bid
Frequency of activation	1x in 2 dagen
Prequalification process	No PQ-test,
Delivery location	Specific connection points or in a TSP portfolio

1.2 Balancing markets

The balancing markets can best be explained by describing how they operate in consecutive order during an imbalance occurrence. ENTSO-E (2019) has visualized the balancing process in a clear overview(see Figure 3 below) which will be used within this chapter to explain the various markets and their related verification methods. As can be observed, the process starts with an imbalance occurrence during a certain time period. The difference between supply and demand in the electricity grid causes the frequency to start deviating from 50 Hertz. As it is the role of the TSO to keep the frequency deviation within a prescribed bound, the TSO activates a set of products in order to avoid further frequency deviation and restore the frequency to 50 Hertz. This set of products is acquired through various balancing markets which will be described in more detail below.

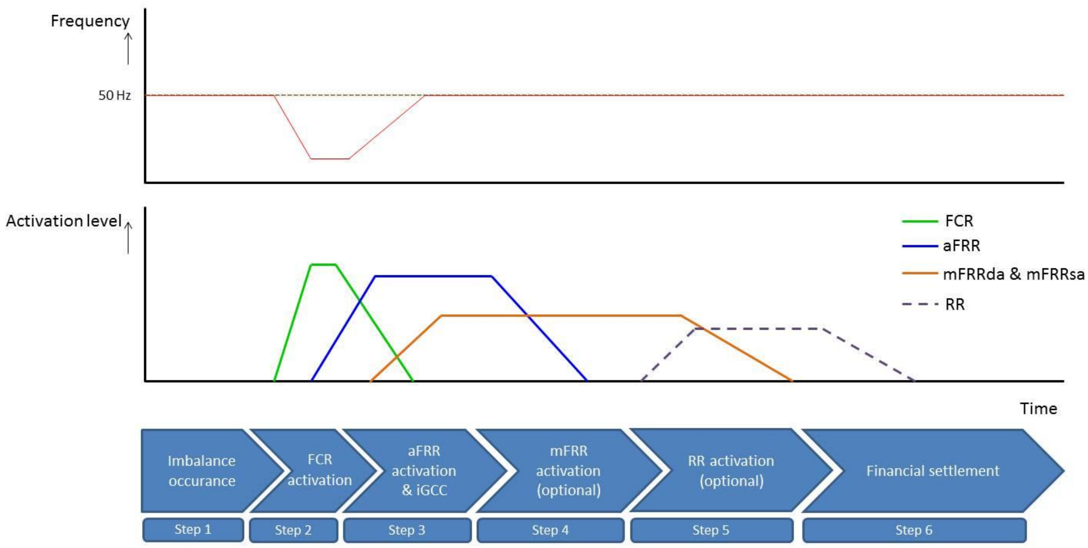

Figure 3: Overview of different steps with the related balancing products from the TSO

1.2.1 Imbalance occurrence

The majority of continental Europe can be regarded as one big electricity system as it is one big synchronous area in which the alternating current (AC) frequency is the same. This is due to the fact that all countries are connected with AC connections. The AC frequency is determined by the rotating masses which are connected to the grid. When there is oversupply in the system they accelerate causing the frequency to go up. While during the event of a supply deficit, they slow down causing the frequency to drop. As the whole area is synchronously connected this inclines that an oversupply or undersupply caused in one country will cause a frequency deviation in the whole synchronous area. The Netherlands is part of the Continental European (CE) synchronous area which is displayed in Figure 4. Synchronous areas are split in different Load Frequency Control (LFC) sections which generally house one country. The Netherlands is one LFC area with TenneT as TSO operating this LFC area. Within this area the TSO is responsible for restoring the imbalance. Imbalance occurs when the total amount of production and import does not match with the total amount of consumption and export. Total production, consumption, import and export is the result of all the summed BRP portfolios within this LFC area. Each BRP needs to have a balanced portfolio and is liable of informing the TSO regarding their planned production and consumption within this portfolio. BRPs can correct imbalances within their own portfolio till the imbalance settlement period (ISP) ends, which is up till 15 minutes before the moment of actual operation in the Netherlands. They can do this by adjusting production and consumption units within their own portfolio or by trading with other BRPs through the various markets. Thus, when they are not able to balance their portfolio before the ISP ends, an imbalance occurrence starts. Generally an imbalance in a portfolio of a BRP can occur when; a generator fails, there is a forecast error in wind prediction or unpredicted consumption change takes place. In case the summed imbalances of the BRPs cause an imbalance of the system as a whole and cause a change in the frequency, the TSOs need to take action to restore this frequency.

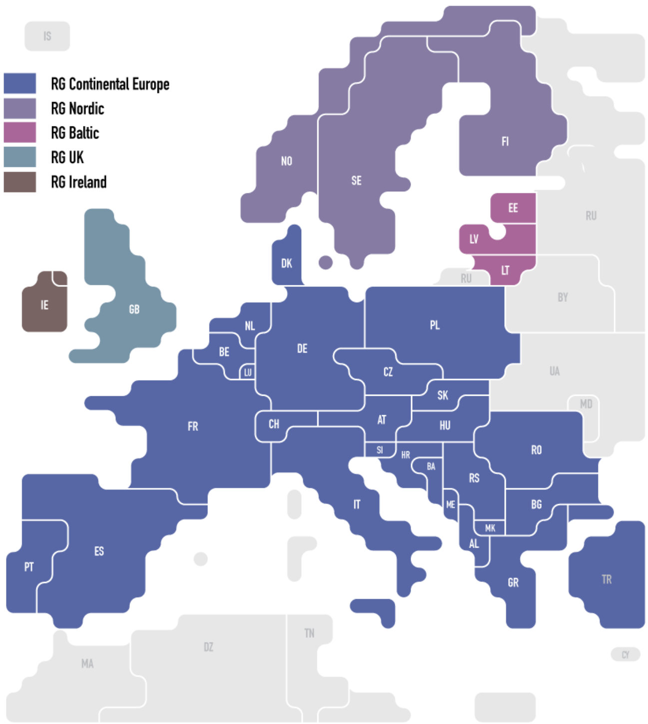

Figure 4: Regional groups in Europe (ENTSOE, 2019)

1.2.2 Frequency Containment Reserve (FCR)

Frequency Containment Reserve is the first resort for the TSO to remain balance within the system and is also known as primary control. When an imbalance situation occurs, the first concern of the TSOs is that the frequency deviation caused by the imbalance is stabilized. This means that the TSO wants to avoid that the frequency deviates further as this can induce damage to electrical appliances which are connected to the grid. Stabilizing the frequency is done by activation of FCR capacity in the opposite direction of the imbalance. The delivery of FCR happens continuously and automatically. A device which reacts on the frequency change, automatically activates the FCR capacity of a provider (TenneT, 2019a). While the grid of Continental Europe is synchronous, FCR is activated automatically all over this area when a frequency deviation occurs. Thus, when anywhere in the Continental Europe an imbalance (e.g. a plant failure) takes place, FCR capacity all over Europe will react to stabilize the frequency deviation. The offered FCR capacity requires a full activation time of 30 seconds and a 50% activation time of 15 seconds and should be able to hold this capacity for a maximum of 15 minutes. The frequency deviation steers the percentage of activated capacity. When the frequency deviation is 200 mHz or more, 100% of capacity is activated. While at a frequency deviation of 100 mHz, 50% of the capacity is activated.

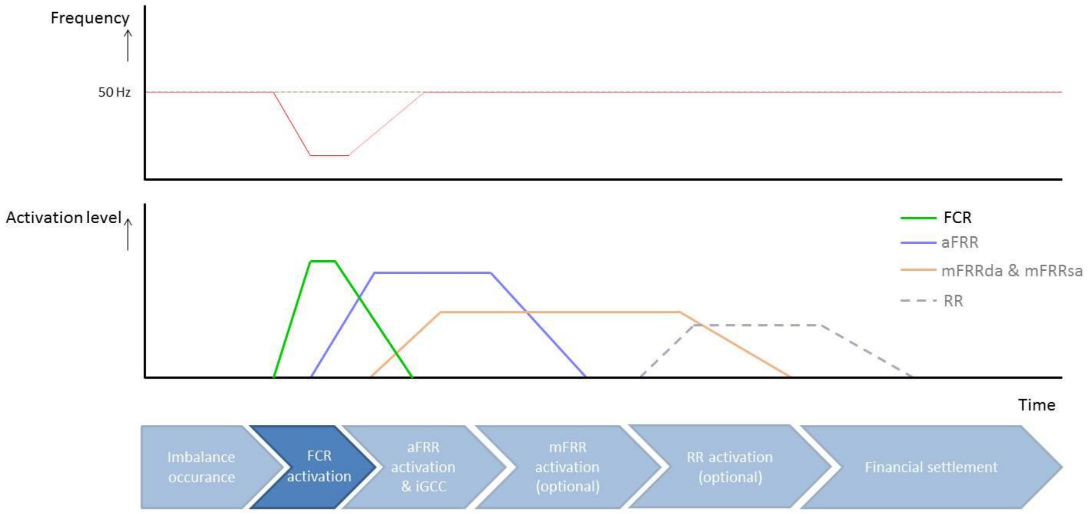

Figure 5: FCR activation

The required FCR capacity is determined for the synchronous CE grid as a whole by the ENTSO-E. They base the required FCR capacity on the largest likely imbalance event in the area, namely a simultaneous outage of the two largest producers in this area. In case such a simultaneous outage occurs the frequency deviation should not exceed -+ 200 mHz. This results in a total need of 3000 MW FCR capacity in both upward as downward direction (TenneT, 2019a). To determine the capacity requirement for each LFC area, the frequency bias is used. The frequency bias is the relative contribution of the LFC area to "the sum of net production and net consumption of the total synchronous area over a year" (TenneT, 2019a). While the Netherlands has a frequency bias of 3.7%, TenneT needs to have 111MW of FCR capacity available at any time during 2019 in both directions (TenneT, 2019a).

To contract the required capacity, most TSOs use auctions. TenneT uses daily auctions to procure the required 111 MW FCR capacity for the Netherlands. From the total FCR capacity TenneT needs to contract at least 30% within the Dutch LFC area. The rest of the capacity can be procured in other LFC areas. In order for a installation to provide FCR capacity it needs to be part of a Balancing Service Provider (BSP). This BSP needs to have a minimum bid size of 1 MW and be prequalified before it is able to bid at the auctions. In order to be able to start delivering FCR, an electronic device responding to the frequency and a hardwired direct line to TenneT is required to communicate the measurement data. During the prequalification the BSP has to perform a set of tests in order to show it capability of delivering the FCR capacity within the required specifications. In 2019 there were 11 BSPs prequalified to deliver FCR (TenneT, 2019b). The delivery of the FCR capacity can be done with a Reserve Providing Unit (RPU) which is a regarded as one or more Technical Installations (TI) linked to a common connection point on the grid. For example a wind park with multiple wind turbines but one grid connection. Besides, FCR capacity can also be provided with a Reserve Providing Group (RPG) which is a group of TIs linked to multiple connection points (see Figure 6) (TenneT, 2015).

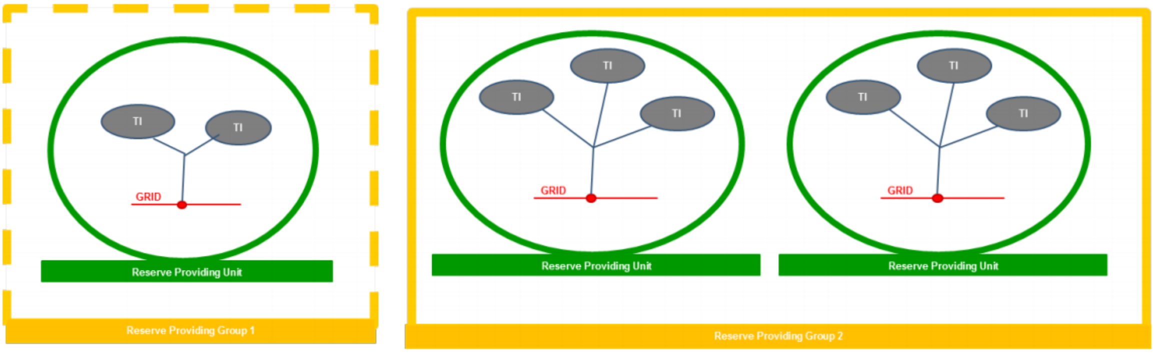

Figure 6: Reserve providing groups and Reserve providing units (TenneT, 2015).

When a BSP passed the prequalification process, it is allowed to make bids on the FCR auctions. During the daily auctions organised by TenneT, FCR capacity is contracted for the 24 hours of the next delivery day (D). Gate opening of an auction is D-14 and the Gate Closure Time (GCT) of the auctions is D-1 at 15:00 (see Table 3 below). As the bids are made for capacity alone, the compensation is also only based on the capacity provided and not for the amount of electricity generated/consumed. The planning is to move from 24 hour delivery periods to six four hour products per day. This would lead to the blocks: 0-4h, 4-8h, 8-12h, 12-16h, 16-20h, 20-24h which will be implemented on the 1st of July 2020 (Kooijman, 2018).

GCT 15:00 (CET)[10]	Monday	Tuesday	Wednesday	Thursday	Friday
Delivery (D)	Wednesday	Thursday	Friday	Saturday Sunday	Monday Tuesday

Table 3: Current Gate Closure Time(GTC) and auction days for delivery days of FCR capacity (TenneT, 2015)

Table 4:Summary of the main characteristics regarding FCR

Minimum capacity	1 MW (upward and downward)
Maximum start up time	Direct
Full activation time	30 seconds
Ramp rate	50 % of capacity in 15 seconds
Method of activation	Automatic activation through electric device reacting on Frequency
Minimum time of continuous delivery	15 minutes
Capacity requirement for the Dutch LFC area	111 MW symmetrical (2019)
Contracting method	Daily capacity auctions
Financial settlement	Compensation for capacity only (€/MW/day)
Frequency of activation	Continuously
Prequalification process	PQ-test process
Amount of BSPs offering FCR	11

1.2.3 automatic Frequency Restoration Reserves(aFRR)

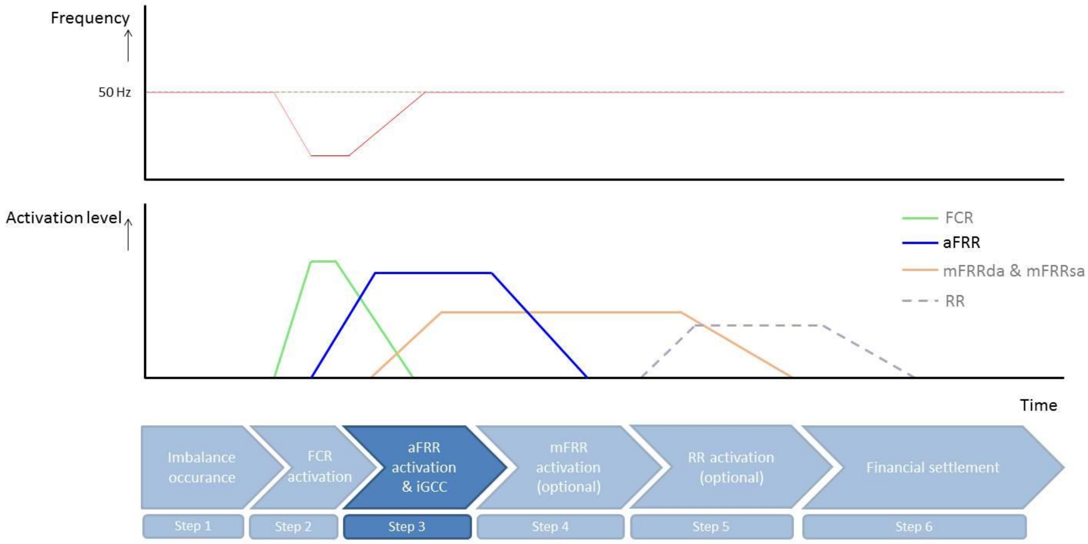

Figure 7: aFRR activation

After that the FCR activation has stabilized the frequency and keeps it within the safety bound, something needs to happen to restore the imbalance and bring the frequency back to 50 Hz. As the activation of FCR capacity lasts for a maximum of 15 minutes, within this timeframe other capacity needs to be activated to take over. Usually this FCR capacity is replaced by automatic Frequency Restoration Reserves (aFRR) formerly known as secondary control or regulating power. Although a local imbalance within an LFC area leads to activation of FCR in the whole CE synchronous area, the LFC area needs to restore this local imbalance within its own area using aFRR. To control the balance within the LFC area an automatic Load Frequency Control(LFC) system is used. In case of the Netherlands this system is called FVR(Frequentie Vermogens Regeling). It calculates the control error continuously which consists mainly of the unplanned international exchange. This is calculated by taking the difference between the total planned cross-border exchange and the total measured exchange on all the international connections with the CE synchronous system. This unplanned international exchange is then corrected by the expected Dutch FCR delivery to determine the final control error. The FVR determines the demanded amount of aFRR energy. Based on this demand the FVR sends set points every four seconds to the aFRR suppliers which indicate how much power to activate and in which direction. The maximum start-up time is 30 seconds and the load needs to be fully activated in 15 minutes in order to replace the FCR in time. The up and down ramp rate is at least 7% per minute to ensure fast enough response. In this way the FCR becomes available again in case another incident happens.

The Continental Europe Operation Handbook prescribes a method to determine the minimum required aFRR capacity for each LFC area. Based on this method TenneT requires a minimum of 385 MW in both directions during the 3th and 4th quarter of 2019 (TenneT, 2019a). In order to obtain the required aFRR capacity in the Netherlands, TenneT uses capacity contracts. These are contracts with a BSP in which a BSP commits to make bids with the contracted capacity during the whole contracted period. To obtain these capacity contracts, TenneT organises monthly and weekly auctions. As a result of EU legislation, from January 2020 all aFRR capacity should be auctioned on a daily basis (Duijnmayer, 2019). The aFRR providers need to be prequalified as BSP and have a minimum bid-size of 1 MW. In 2019 there were 4 BSPs prequalified for delivering aFRR (TenneT, 2019b). The offered aFRR capacity can be aggregated over several assets which together provide the up and downward capacity. When a provider has won the capacity auction, it is forced to offer this capacity by making bids ultimately D-1 before 14:45 for all ISPs of the next operation day. The maximum bid price for upward regulation is EUR 1.000 per MWh while for downward regulation it is EUR -1000 per MWh. After these obliged bids for each ISP of the next operation day are approved by TenneT, the BSPs are allowed to modify the bids till 30 minutes before each ISP. The suppliers of this contracted capacity get compensated for reserving this capacity and making these obliged bids. Afterwards, when these bids are activated, they also get compensated for the energy they deliver.

Besides the contracted aFRR, BSPs are also able to make so-called free-bid. These free-bids can be made voluntary for an ISP in which the BSP has capacity available. These bids can be made ultimately 30 minutes before the ISP begins and will be taken along in the bid-ladder with the contracted bids. Besides the 4 BSPs registered to offer contracted aFRR there are two more parties which are only prequalified for making non-contracted bids. Thanks to this relative short lead-time it offers a chance to aFRR providers with a higher uncertainty. Especially renewables don’t have much certainty about their long-term production because of stochastic dependencies. Besides, the fact there is an uncertainty about their production, their production is also variable which makes it hard to guarantee a certain capacity with 100% certainty for a long period of time. Therefore, with these voluntary bids which have a short lead-time and a limited period of continuous delivery offer a chance to renewables to offer balancing capacity.

The suppliers making these free-bids get compensated for the activated energy alone. These free and contracted bids together form the new bid-ladder on which the aFRR price is determined for each ISP. The remuneration for all activated aFRR energy happens on the price level with the highest price delta. The LFC system determines the bids to be activated based on the new bid-ladder and sends power set-points to the BSPs providing the aFRR which indicate the requested upward or downward volume. These set-points represent the requested volume on top of the normal energy profile of the BSP based on its portfolio. The BSP needs to follow these set-points in order to deliver the requested aFRR volumes.

Table 5: aFRR specifications

Minimum capacity	1 MW
Maximum start up time	30 seconds.
Full activation time	15 minutes
Ramp rate	7 % of capacity per minute
Method of activation	Automatic activation through LFC system
Minimum time of continuous delivery	15 minutes
Capacity requirement for the Dutch LFC area	425 MW symmetrical (Q1-2 2019) 385 MW symmetrical (Q3-4 2019)
Contracting method	Monthly and weekly capacity auctions Participants which have won the auction are obliged to bid for providing aFRR energy every ISP for the next day.

	Free bids can be submitted up to one hour before aFRR activation.
Financial settlement	Compensation for capacity auctioned (€/MW/month) or (€/MW/week) Compensation for energy supplied or consumed (€/MWh)
Prequalification process	PQ-test process
Amount of BSPs offering aFRR	4 for contracted aFRR and 6 for non-contracted aFRR

1.2.4 manual Frequency Restoration Reserve (mFRR)

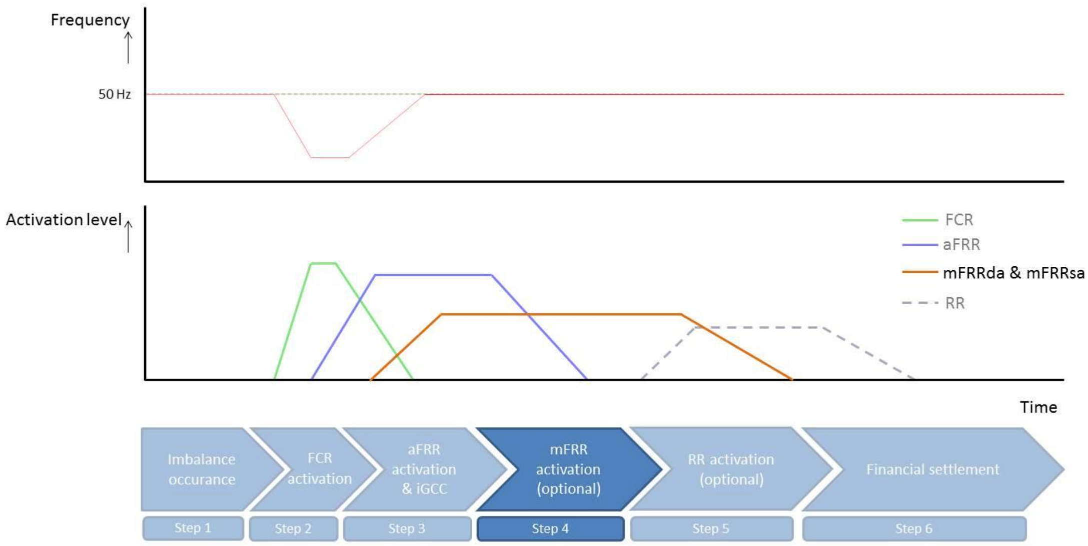

Figure 8: mFRR activation

In case of incidents or long –lasting power deviations, manual Frequency Restoration Reserves(mFRR) can be used. Formerly mFRR was known as reserve power or tertiary control. As the name already suggests, mFRR is not activated by a computer system but manually by the operators in the control room. The goal of mFRR is to relieve aFRR and make it available again for new imbalance occurrences. Therefore, the activation of mFRR does only occur when there is a endured activation of aFRR.

There are two forms of mFRR which can be differentiated, namely directly activated mFRR (mFRRda) and schedule activated mFRR (mFRRsa). For mFRRda the requirement is that it needs to deliver the capacity immediately from the moment of activation. From that moment capacity needs to be fully activated within a maximum of 15 minutes for upward capacity. For downward capacity the full capacity need to be activated within 10 minutes. From the moment of full activation, the capacity needs to be able to stay activated for at least 60 minutes. Hence, while this capacity needs to stay reserved all the time mFRRda is contracted by way of capacity contracts. While mFRRda requires immediate activation, mFRRsa are offers for specific ISPs. A provider can make offers for a self-preferred set of ISPs with a minimum of one. The activation will take place one or two ISPs before the ISP of interest so the provider is able to prepare activation of the capacity. While the bids are made voluntary mFRRsa is con contracted capacity. This extra to the contracted capacity but will be integrated within the bid-ladder similar as free aFRR bids.

For the Dutch LFC area a minimum of 685MW upward and 629MW downward mFRR capacity was required during the last half year of 2019. To contract this capacity, TenneT organizes a monthly and a weekly auction in which it contracts mFRRda capacity. Both account for 50% of the contracted mFRRda capacity in the Netherlands. According to EU legislation, from September 2020 all capacity should be auctioned on a daily basis (Duijnmayer, 2019). As a result of the this shorter lead-time and capacity delivery period, there will be more opportunities for intermittent renewables to offer mFRRda.

Table 6: mFRR specifications

	mFRRda	mFRRsa
Minimum capacity	20 MW	1MW
Full activation time	15 minutes >> Or as specified	Beginning of offered ISP
Method of activation	Phone call by operator and an electronic message	Phone call by operator and an electronic message
Capacity requirement for the Dutch LFC area	720/652 MW (up/down) (Q1-2 2019) 685/629 MW (up/down) (Q3-4 2019)	None
Contracting method	Monthly and weekly capacity auctions Participants which have won the auction are obliged to bid for providing mFRR energy every ISP for the next day. Free bids can be submitted up to one hour before aFRR activation.	None/Voluntary bids
Financial settlement	Compensation for capacity auctioned (€/MW/month) or (€/MW/week) Compensation for energy supplied or consumed (€/MWh)	Compensation for energy supplied or consumed (€/MWh)
Prequalification process	PQ-test process	No PQ-test
Amount of BSPs offering mFRR	12	5

Chapter 2: Verification of the delivered AS

TenneT operates in the AS markets as a single buyer. It pays for the capacity which it actions through these various markets. This chapter discusses the relevance of verifying whether this actioned capacity was correctly delivered as contracted. Furthermore, it discusses which methods are currently applied to verify the correct delivery of the different AS discussed in the last chapter. Accordingly, the following question will be answered in this chapter:

“What is the relevance of verification of correct delivery of actioned AS capacity and what methods are used for this?”

In order to answer this question, first the general relevance of verification of delivery will be discussed. Thenceforth, for each of the five different AS products the specific relevance will be reviewed and when in place, the existing verification method will be described.

2.1 Relevance of verification

As defined in the previous chapter, the key objectives of the TSO are to maintain the integrity, safety and stability of the transmission grid. The AS are products that the TSO buys in order preserve a well-functioning electricity system. When AS providers would not correctly deliver the capacity, this can jeopardize the electricity system. This is the first and most important relevance of verification of delivery; to monitor if the AS provider did not expose the system to a risk. Secondly, when providers know there is a verification on delivery, this incentivises them to properly deliver. Especially when non-delivery causes a penalty or has other consequences for the provider. As the AS providers are market parties, their main purpose is making profit. Therefore, when they can make more money when not delivering the capacity, there is an incentive for them to do this. It can be beneficial for providers to not deliver the requested AS capacity for several reasons. For example they avoid paying fuel costs, sell the non-delivered capacity on another market or use the capacity to balance their BRPs portfolio. Strategic behaviour in electricity markets has been observed in different countries and systems (Kleindorfer et al., 2001). Hence, there is relevance in verification of delivery while otherwise market parties would be unrestricted to not deliver or improperly deliver the requested capacity. From the TSO perspective, you can also argue that verification of delivery helps to evaluate whether the product you buy meets the set requirements. As the TSO pays for a certain product, they want to check if they get value for their money. Furthermore, if the actioned capacity is not delivered, the problem this capacity should to solve will not be solved. As a result, the TSO will have to buy more capacity in order to solve the problem and therewith pay two times for the same capacity. This increases the overall costs to operate the system. As the TSO costs will ultimately be included in the transport costs of electricity, the end consumer will eventually pay for it.

For the balancing products, structural verification of delivery is already in place. But despite of the relevance outlined as discussed above, for redispatch no structural verification of delivery happens. Hirth & Schlecht (2019) have recently demonstrated in their study that market based redispatch inevitably leads to gaming behaviour of market parties. Their study shows that: “market parties anticipate the redispatch market and bid strategically in the spot market – the so-called increase-decrease game. As a result, grid congestion is aggravated, producers extract windfall profits, financial markets are distorted, and perverse investment incentives emerge” (Hirth &

Schlecht, 2019, p.1). When incentives for gaming the redispatch market exist, the relevance of verification in the redispatch market also becomes evident. No clear evidence of such strategic gaming behavior in the Dutch redipatch market is decribed in literature or was officially reported. However, as in the Netherlands redispatch is procured in a market based way, the study of Hirth & Schlecht (2019) suggest that this type of behavior is inevitable in the Dutch market system but was simply never officially observed.

2.2 Current verification methods

2.2.1 Redispatch

Currently, no structural verification happens for redispatch at TenneT. The BRPs portfolio does get corrected for the actioned redispatch. Therefore, when a provides does not deliver the redispatch capacity, it will have to pay the imbalance price for the non-delivered amount. Nevertheless, this imbalance price can be lower than the price it receives for the redispatch action. It can even be the case that the imbalance which is created by non-delivery of the redispatch action supports the system. In that case they would even receive money for not delivering the redispatch capacity. Furthermore, as no verification of delivery happens, the redispatch capacity can also be delivered on another location. In that case the provider will not have an imbalance in its portfolio but also not support the TSO on the location where the capacity was required. When the capacity is delivered in the wrong area, the congestion problem can even be aggravated. As no market incentive is in place for the redispatch providers to properly deliver the redispatch capacity, verification of delivery seems very relevant.

2.2.1.1 GOPACS

Although no structural verification of delivery happens in the redispatch markets. GOPACS has the intention to perform verification on its platform in the future. As the GOPACS platform is relatively new and currently mainly focusses on expanding, no structural verification of delivery is performed yet. The intention is that the grid operator which operates the grid on which the ordered volume is delivered should verify the delivery of the energy. The delivered energy is relative to the delivered T-prognosis of the asset. When the T-prognosis is not available it should be relative to the 'generation and load schedule' as requested regarding EU legislations. When there is no planned generation or load available, the market party should agree with the concerned grid operator how to deliver a load and generation schedule (GOPACS, 2019a). Accordingly, when the asset has a certain T-prognosis or other generation and load schedule, the IDCONS is actioned based upon this prognosis. Therefore, the measured exchange on the indicated EAN location is compared with the delivered prognosis. In the future all connections with a capacity of 1MW or more should deliver a T-prognosis (Liander, 2019).

If the validation process indicates that a market party does not meet de requirements of a proper delivery as indicated within the IDCONS, the related grid operator will address this issue to the market party. As the project is still in the pilot phase, no fines are currently issued. The level of the fine in the future is still unknown.

2.2.1.2 Reserve Power Other Purposes

For ROD, there happens no structural verification regarding the delivery of redispatch capacity. The system operations department indicates that the reason for this is that they can see this in the actual operation of the system. Because the actioned redispatch is historically provided by large generators by large volumes at once, the effects of these actions can be observed in the SCADA data which monitors the grid of the TSO. Nevertheless, when the actioned volumes are relatively small it becomes impossible to observe. For this reason, as GOPACS tends to focus on smaller assets providing smaller amounts of redispatch volume, verification seems more relevant there. Nonetheless, while the minimum bidding volume in ROD is 1MW, also smaller volumes are actioned on this platform.

2.2.2 Balancing Markets

For balancing products structural verification is already in place and happens on a daily basis. The different methods vary a bit related to the specific requirements of the different products.

2.2.2 FCR

For FCR the verification happens visually by a TenneT employee which monitors the output of a FCR provider ex-post. The FCR capacity can either be delivered by a RPU or RPG. As the FCR delivery happens automatically by the RPU or RPG based on the frequency, the key objective in verification of delivery is whether the response to the frequency happened properly. The expected response of a RPU or RPG can be calculated based on the amount of capacity they offered and the change in frequency. This expected output can be compared with the measured output of the RPU or RPG. While the FCR is the fastest response mechanism, TenneT also wants to verify whether this response happened fast enough. Through the direct connection with the TSP they get the measurement data of the providing RPU or RPG on a 4 second time interval. Based on this time-scale they are able to verify the delivery to simply compare the response of the RPU or RPG to this actual measurement data.

Table 7: Specification verification method FCR

Timescale metering data	Maximum of 4 seconds, if possible 1 second
Level of metering data	At RPU or RPG level
Validation methodology	Compare response of RPU/RPG to frequency at this moment
Level of automatization	Visual inspection by TenneT employee

2.2.4 aFRR

In order to determine whether the requested aFRR volume was actually delivered, real time metering data of the aggregation from the BSP and their scheduled power exchange are requested. To send the set points and receive the real time measurement data, TenneT needs a direct physical connection with the BSP. The scheduled power exchange of a BSPs aggregation is delivered by this BSP to TenneT as a reference signal. The reference signal indicates the expected load according to its own energy program one minute later. Complete or partial inclusion of the setpoints is not allowed as it prevents a fair assessment of the realized aFRR delivery. Consequently, for each four second time point, TenneT receives the actual measurement data and the reference signal for one minute later.

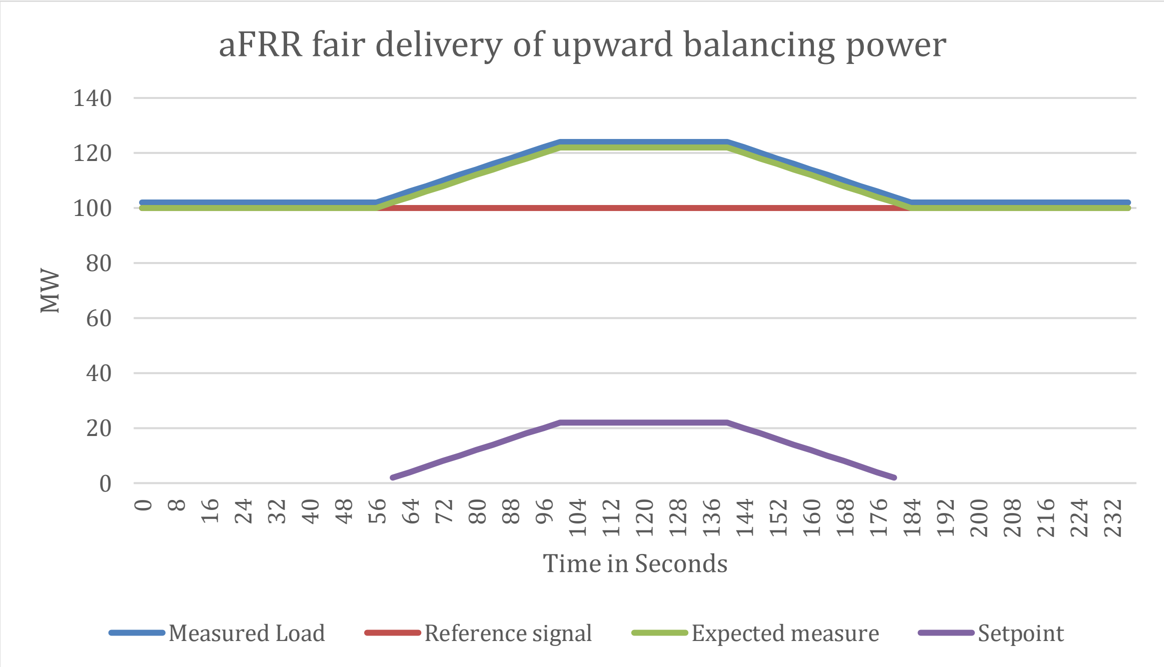

Figure 9 Example of fair delivery of aFRR power as requested by TSO

To verify delivery, TenneT will compare the reference signal with the actual measurement data at the coinciding time point. When the difference between the two matches the volume of the set-points, this indicates a proper delivery. Figure 9 indicates how this process works in theory for upward balancing power. In normal operation the reference signal should match the measured load as it represents the normal operation according to the portfolio of the units in the aggregation. Therefore without aFRR activation the expected load is equal to the reference signal. When the TSO starts sending setpoints for the delivery of aFRR power, the expected load is equal to the reference signal plus the absolute value of the setpoint.

Monitoring on proper delivery happens on a daily basis by process specialists. They observe the graphs in which the actual measurement is compared with reference signal and the expected load. It can then be observed if the BSP follows the desired profile. In Figure 9 an example is given of a fair delivery of upward aFRR volume in which the aggregation neatly follows the expected measure. A non-delivery can be observed in Figure 9. In this case the actual measured load does not follow the expected load according to the setpoints. When an incident like this occurs it is clear for the process specialists that there is a situation of non-delivery. When this is observed for capacity contracted aFRR, this means that the contracted delivery was not delivered within the aggregation. At first, TenneT generates a report which is sent to the supplier to explain about the reason for inappropriate response. It can be the case that the capacity was delivered with a unit outside of the aggregation due to technical constraints. If this is the case it needs to be proven with extra measurement data that the power was delivered at another unit. When the power was not delivered this implies that the contract was broken which can lead to fines specified within the contract between the TSO and BSP. For the non-contracted aFRR no fines are granted as these bids are voluntary. Therefore no payment for the capacity is made and the provider does not get compensated for this. When an non-contracted BSP performs multiple non-deliveries this can lead to excluding this BSP from making free bids.

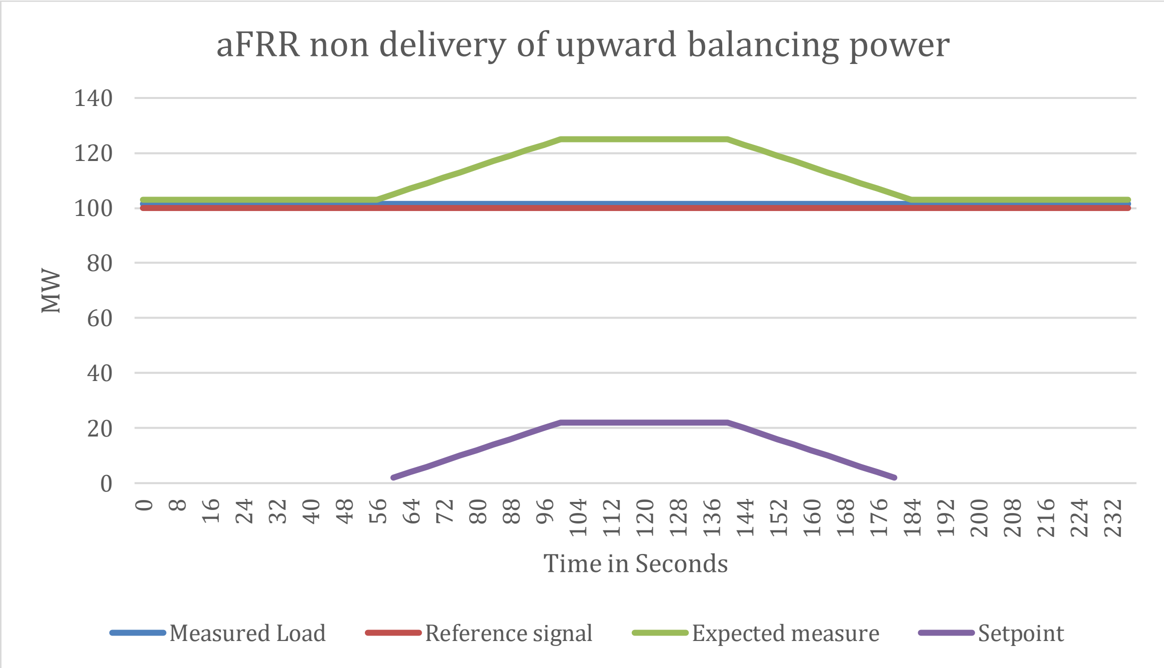

Figure 10 Example of non-delivery of aFRR power as requested by TSO

As a BSP is an aggregation of assets, the metering data is acquired on the aggregated level of the BSP. While the combination of different assets together can provide the balancing capacity, a BSP determines how this requested volume is scattered over the different assets within the aggregation. For this reason the verification also happens on the aggregated BSP level. A BSP is able to change the units within the aggregation, this means that during the day the pool of units can change and the according measurement and reference signal. This makes it harder to verify if the reference signal as the pool of assets is changing over time.

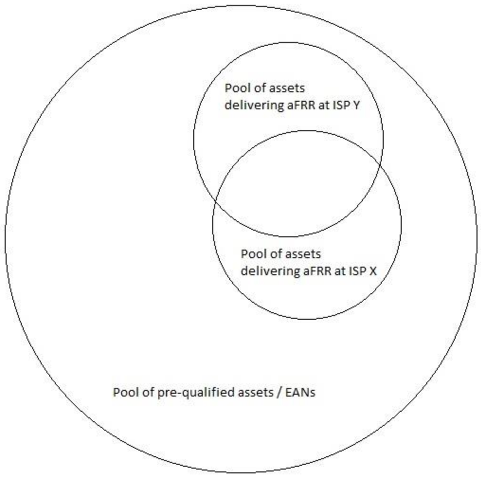

Figure 11 Pools which deliver aFRR capacity

The BSPs get payed for the delivered energy times the imbalance price during this ISP. As this extra upward or downward energy delivery by the different assets causes an imbalance within their BRPs portfolio's, this will be corrected afterwards on their E-program. The risk of gaming with the baseline during an activation is considered low since the direction and variability of the activation is not known one minute in advance and since the set-point is sent every 4 seconds, this direction can rapidly change. In order to apply gaming, the aFRR provider has to correctly forecast the direction of the aFRR request at least one minute in advance.

Table 8: Specifications verification method aFRR

Timescale metering data	4 seconds
Level of metering data	Aggregation on BSP level
Validation methodology	Use of a reference signal
Level of automatization	Visual inspection by TenneT employee
Prequalification process	PQ-test process

2.2.5 mFRR

Similar to aFRR, mFRRda can also be offered in an aggregation of assets. Differently from aFRR the pool of mFRRda providers is a pool which is not as flexible as with aFRR. The assets within the aggregation are registered per EAN. The metering data is acquired on EAN level but the mFRR capacity is offered on an aggregated level. This inclines that the mFRR is offered on an aggregated level, with a combination of assets but the verification is done on an EAN level.

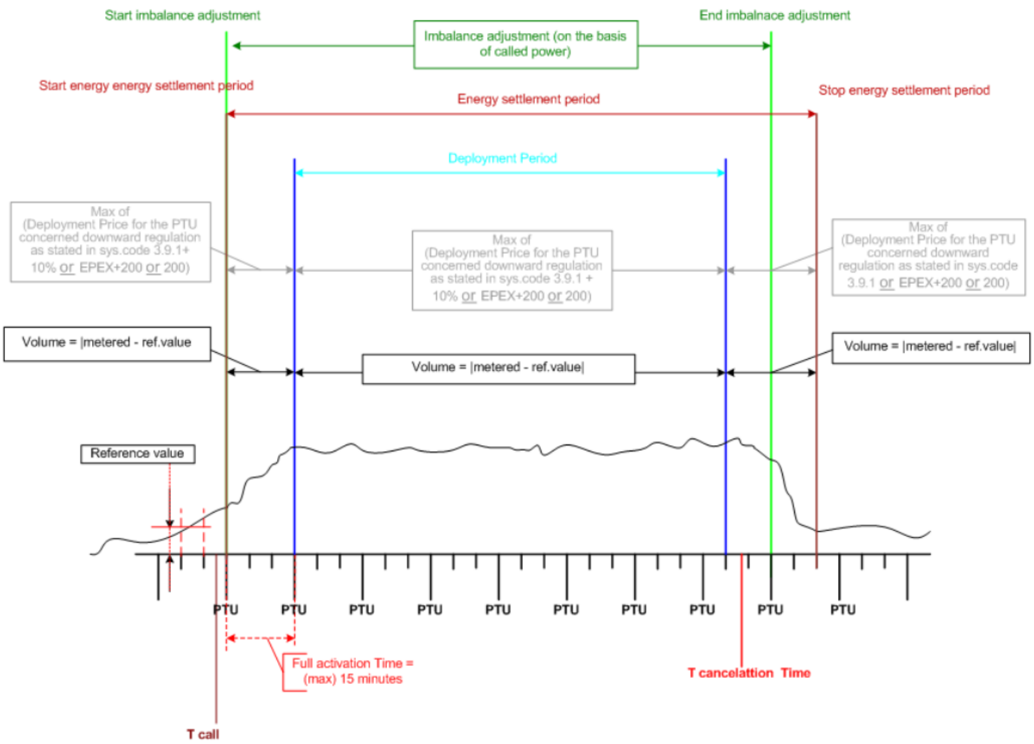

Figure 12 Example of verification method regarding upward energy delivery for mFRRda

The method for verification of mFRRda capacity is relatively straight forward. It simply uses the average exchange with the grid during the last five minutes prior to the activation of the capacity. This amount is used as a reference for determining the capacity a unit delivers. In contrary to the method for aFRR, this method does not take the schedule of the unit into account. It simply takes the exchange before activation as a reference for the entire activation period. The time scale of the metering data is five minutes. For every five minutes the redispatch amount which is activated should be delivered relative to the reference. The method can be observed in Figure 12.

Table 9: Specification verification method mFRRda

Timescale metering data	5 minutes
Level of metering data	RPU or EAN level
Validation methodology	Use of a reference value
Level of automatization	Fully Automated

Chapter 3: Ancillary services delivered by wind

This chapter discusses the technical capability and relevance of wind power participating as AS. It examines the role of wind turbines in the electricity system in terms of offering supportive capacity. It reviews what type of AS are already delivered by wind assets and which methods exist to verify this delivery. Therewith trying to answer the following research question:

"How do wind assets participate in AS markets and which methods are used to verify the delivery of AS capacity delivered by wind assets?"

Renewables are gradually putting conventional generation units out of place in terms of electricity dispatch. As these conventional generation units are also the traditional providers of AS, there is an increasing necessity of renewables providing AS in order maintain the stability and security of electrical systems (Fernandes et al., 2016). While the Dutch Climate Agreement (Klimaatakkoord) states to target for 70 percent of renewable electricity generation in 2030, the urge of renewables providing AS in the Dutch electricity system becomes evident (Rijksoverheid, 2020). Within these targets, wind energy is assumed to provide the largest share of renewable generation, including 11 GW installed offshore wind capacity by 2030 (Rijksoverheid, 2018). Next to the expectation that the increasing share of renewables will cause a reduction of conventional AS providers, these renewables are also expected to create an extra demand for AS capacity. As Vandezande et al. (2010) argue: "the presence of wind power in a system increases the need for regulating and reserve power in order to handle its variability and limited predictability. As indicated by various studies, balancing power requirements are expected to increase proportionally with growing wind power penetration" (p. 3146). Therefore, within Dutch electricity system, there will be an increasing need for wind offering capacity for AS in the near future.

Generally, wind assets are regarded as passive producers which produce when there is wind irrespectively of the demand in the system. Sorknæs et al. (2013b) argue that: "wind power should not only function as a passive producer, but instead be a proactive producer that helps reduce imbalances in the electricity system, and reduces production in situations with excess electricity in the electricity system. In that way wind power will both be active in the electricity system balancing tasks, and be proactive by reducing the balancing impact of the forecast errors'' (p. 174). From an economical perspective, wind turbines will only offer downward AS capacity as their marginal costs are zero. Therefore, they will always try to sell all anticipated power production on the energy markets when day-ahead prices are positive. In case of offering upward capacity, wind turbines would have to continually curtail their production output which is at no cost. Only during the exceptional occurrence of sufficiently negative prices on the day-ahead market, when wind turbines are deliberately closed down, they could offer upward capacity (Sorknæs et al., 2013a). Nevertheless, these occurrences are very rare, hence within this research only downward regulation is regarded.

Numerous studies and pilot projects demonstrated the technical capabilities of wind assets to provide downward capacity for various types of AS. Sorknæs et al. (2013a) showed that a 24 MW wind farm in Denmark was perfectly capable of providing mFRR. In Germany a study also demonstrated the technical capability of wind assets delivering downward mFRR (Mackensen et al., 2017). A pilot project at the Estinnes wind farm in Belgium showed wind can also provide aFRR (ELIA, 2015). Also in Germany and Spain aFRR has proven to be a reliable asset for providing aFRR (Fraunhofer IWES, 2014; TWENTIES Project, 2013). Wind assets have even evidenced to be accurate and responsive enough to deliver FCR (National Grid ESO, 2019; Ørsted, 2016). Wind curtailment as a form of congestion management has already sustained its technical capability as it is already commonplace in daily operation in countries like Scotland, China, Spain and Germany (Edmunds et al., 2019; Joos & Staffell, 2018; Martin-Martinez et al., 2014; Song et al., 2019; Xia et al., 2020). Although this research focusses on response, reserve and congestion services, it ought to be mentioned that wind assets are competent to deliver other ancillary services, comprising voltage control, power oscillation damping, reactive power, and black start (Edmunds et al., 2019; Hansen & Iov, 2016) .

Yet, it ought to be mentioned that in a well-functioning electricity system wind turbines should only reduce their production in extraordinary conditions as curtailment of wind turbines leads to lost energy. When conventional power plants reduce their output, this also decreases the consumption of their input fuels like coal or gas. If a wind turbine is curtailed, this simply implies it does not make use of the freely available wind which can be regarded as lost energy. For this reason, the curtailment of wind turbines should only happen as a last-resort when the flex of all other units is exhausted.

Although wind turbines have been widely integrated within European wholesale electricity markets, the participation on balancing and other AS markets is still limited (Sorknæs et al., 2013b). Fernandes et al. (2016) identify that the barriers to the participation of wind power producers in AS markets are related to the high variability and limited predictability of its production, together with the design of the AS markets which require long time frames for guaranteeing the capacity and a gate-closure which is far ahead of the real operation time. As the variability of wind power production over different hours is considerably higher than the variability within more concentrated timeframes(smaller than 30 min), assuring a certain amount of capacity for a longer timeframe is problematic (Nazir et al., 2012). In a similar fashion, forecasting errors increase when lead times increase as can be observed in Figure 13. Therefore, the further away the real time operation is from the gate-closure, the harder it is for wind asset owners to guaranty a certain capacity.

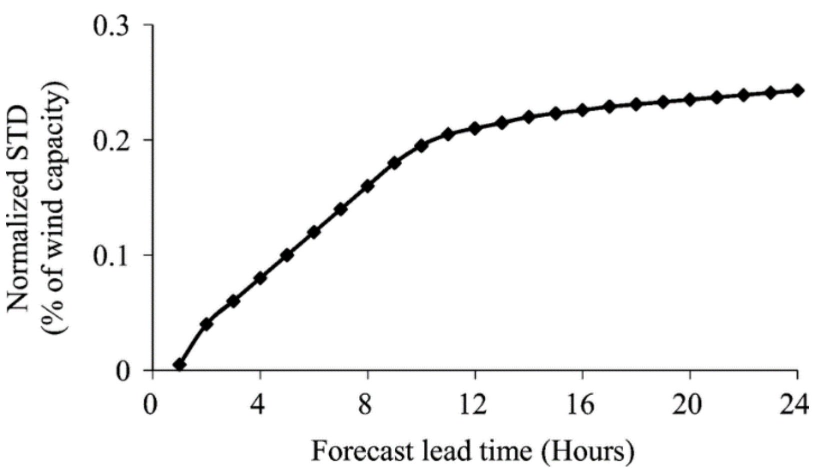

Figure 13: Average forecast error for wind power production by different lead times (Ma et al., 2013).

The above barriers have been recognized by European regulators and according to EU regulations all balancing markets should have auctions on a daily basis from the 1st of January 2020. For the Dutch balancing markets this date is postponed to the 1st of September 2020. This means that for FCR, aFRR and mFRRda the weekly and monthly auctions will move to daily auctions from this date (Senfal, 2020). Therewith, decreasing the product time frames and decreasing the time between gate-closure and real time operation. Although these barriers might be partly reduced by changing market design, there is another barrier which prevents wind assets from offering downward AS capacity. Currently, there are support schemes for wind power production which are linked to their production. In The Netherlands a feed-in premium is added to the market price for each produced megawatt hour during the first 15 years (Hiroux & Saguan, 2010). This means that when a wind asset curtails its production during this period, it loses the feed-in premium for this production. Therefore. when making an offer for downward regulation they will always include this loss of the feed-in premium into the price of the offer. Consequently, the costs for downward capacity from wind assets is relatively high causing that they will not be very competitive within the balancing and congestion markets. This might hinder them from participating or from being actioned within these markets. After 15 years of operation, the wind assets will lose the feed-in premium and offering downward capacity as AS might become more interesting. Currently in The Netherlands the first wind parks are tendered without subsidy schemes entirely taking away this barrier (Rijksoverheid, 2019).

3.1 Verification of downward capacity delivered by wind assets

While the participation of wind assets in offering AS capacity is still very limited, it will increase according to the changing conditions mentioned above. From a TSO perspective it is therefore also important to properly verify the delivery of the actioned capacity. Yet, there are some principal dissimilarities between wind assets and conventional generators delivering AS which ask for a new method of verification. Most important is the difference associated with the reference power from where the AS capacity is performed. Also regarded to as the baseline, or the feed in of the asset if no AS capacity was delivered. For a conventional power plant the producer can define the generation profile of the asset beforehand. When delivering the AS capacity the expected feed in will be the sum of the load defined beforehand and the AS capacity. The load of a wind asset on the other hand, is determined by the weather conditions on the location of the asset. In that case it is more complicated to define the expected feed in of the wind asset in case of AS delivery. Literature describes two methods to define this reference power(or baseline) of wind assets. The first is the ‘Balancing control mechanism’, this method implies to continuously de-rate the production of the wind asset to a production level which is set in advance (ELIA, 2015). In this way the reference load can be delivered ex-ante similar as with a conventional production unit. Although this method is simplistic, the main disadvantage is that the asset will continuously have a loss of renewable generation due to the derating of the production (Jansen et al., 2014). For this reason, this method is not considered as a feasible option within literature and also within this research (Jansen & Speckmann, 2013). A more viable method is the ‘Active Available Power(AAP) mechanism’. This AAP is an estimation of the production of a wind asset if there would be no delivery of AS. This estimation is based on the real-time wind conditions and the technical components of the wind asset. This AAP can then be used as a baseline or reference load.

This AAP method is tested in different studies using the SCADA data of the wind turbines. In order to test the accuracy of the model the estimated production by the AAP method can be compared to the actual production during normal operation (non-curtailed conditions of the turbines). Jansen et al. (2014) showed very high accuracy when testing the method on two German wind parks. The AAP model reached a Root Mean Squared Error of the nominal installed capacity(RMSE) of 2,14% on a 10-minute time interval, 2.37% on a 1-minute time interval and 2,88% on a 3-second time interval. During a test with a Belgium wind park the method showed that on a 10 minute time scale, “the AAP error was, on average, limited to a few percentages of the actual measured feed in” (ELIA, 2015, p. 9).

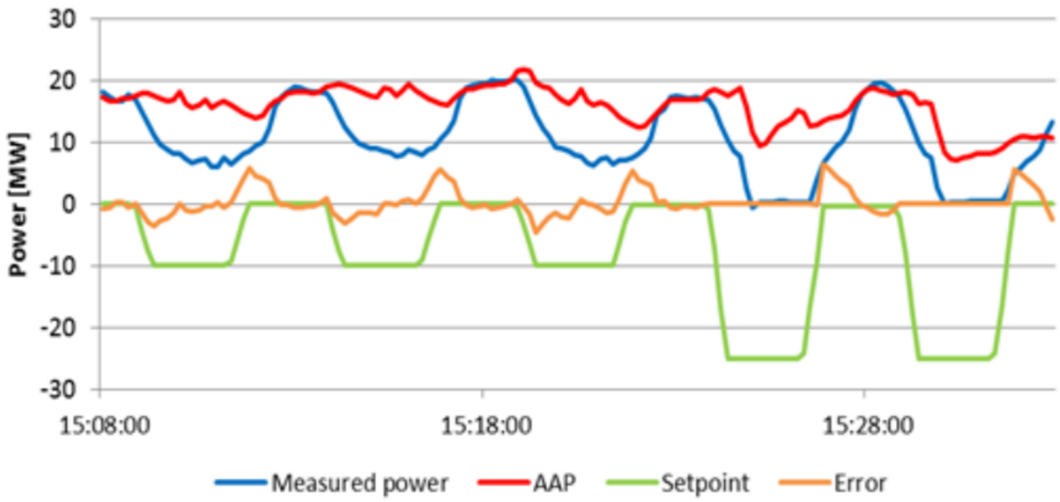

Figure 14: Active Available Power method used on a wind park with downward aFRR requests (ELIA, 2015)**.**

Using this method it should be taken into account that during curtailment of a wind turbine the windspeed downstream of the curtailed wind turbine rises, the so-called ‘wind farm effect’. This downstream turbine may then produce more and somewhat offset the actioned curtailment. Likewise, the anemometer on the curtailed wind turbine is also downstream of the blades and will therefore measure an increased windspeed compared to a non-curtailed wind turbine. This may lead to an overestimation of the AAP. Göçmen et al. (2019) have demonstrated that this problem can be solved by using the windspeed at the upstream wind turbines. Their possible power algorithm showed to be within accurate enough for Danish TSO requirements.

The above mentioned AAP method can be applied for verification of delivery of multiple AS.

Chapter 4: Method for verification of redispatch delivered by wind assets

Related to the increasing demand of redispatch capacity and the opening up of the redispatch market for smaller scale assets, relevance for TenneT to verify the delivery of this redispatch capacity grows. TenneT is searching for a uniform, automated method which uses the existing measurement data stream to verify the delivery of redispatch capacity. As a result, the following research question arises:

“To what extent is it possible to verify the delivery of downward redispatch by wind assets in a uniform, automated way when using public reanalysis wind data?“

In order to answer this question, a method to verify the delivery of downward redispatch by wind assets is proposed in this chapter and tested in the following two chapters.

The increased feed-in of renewable energy sources caused the amount of requested redispatch to increase significantly during the last several years (Tennet, 2019). As the amount of renewables is bound to increase during the coming decade, it is expected that the amount of redispatch volume will be increasing as well. As discussed in *Chapter 3: Ancillary services delivered by wind*, the new wind turbines have the technical capability of derating their power output. Moreover, as new wind parks are built without subsidies, it will be highly likely that wind assets will be delivering more redispatch in the future (Rijksoverheid, 2019). As the GOPACS platform also anticipates to perform redispatch with smaller scale assets to solve more local congestion problems, it is expected that small windfarms, sets of wind turbines or individual wind turbines will also be able to deliver redispatch in the future.

Hence, when these more distributed wind assets start delivering redispatch, it becomes necessary to verify whether the requested amount of redispatch was actually delivered on the right location. As discussed in Chapter 2.2.1 Redispatch, the volumes of the current redispatch bids in RESIN are mostly large enough to see the effects in the actual operation of the grid. However, when smaller volumes are actioned, this cannot be observed by the operators and therefore verification becomes more essential. As there is no current method in use for verification of redispatch, exploring such a new method is desired from TenneT perspective.

As the output of the wind parks is intermittent and highly variable and depending on the weather conditions, based on the measurement data alone it is hard to verify whether the requested amount of downward redispatch has actually been delivered. As the output of a wind park goes up and down continuously, it is hard to tell if the output changed because of changing wind conditions or active steering of the park. GOPACS has been set up as TenneT is searching for an extension of the supplier base and an increase of competition. At the same time, the DSOs hope to use the platform to solve more local congestion problems in their network (Hirth & Glismann, 2018). In order to attain these objectives, it is necessary that smaller assets offer capacity on the platform. For this reason, the verification method should also be suited to verify smaller wind assets which deliver redispatch.

4.1 Design requirements

Concluding from Chapter 3: Ancillary services delivered by wind, it would be possible to simply use the AAP method. It is good to review this existing verification method when developing a method for redispatch. Active Available Power(AAP) is a method which is used to create a baseline to verify the amount of curtailment by wind assets when delivering aFRR. Tests indicate that this method seems accurate and reliable enough to verify aFRR (ELIA, 2015). However, it also requires the data of the anemometers on each individual wind turbine behind the grid connection which delivers the aFRR. This requires the setup of a data stream between the AS providers and the system operator. This involves investments to set up such a data stream, from both the AS providers as the system operator side. These type of transaction costs can be a barrier for wind assets to deliver ancillary services. In the current situation such connections are non-existent in the Netherlands, even for the large wind parks this wind specific data is not shared with the TSO.

A second thought could be to verify the delivery relative to the T-prognosis. As the TSP has to deliver a T-prognosis to the TSO to indicate the expected exchange with the grid, this could be used as a reference and the redispatch delivery can be relative to this T-prognosis. However, the T-prognosis is only an indication of the exchange with the grid but is non-binding. In the Netherlands grid users have the freedom of dispatch, what means that they are free to consume or produce with their connected assets the way they want. Only the total energy program of the BRP for each ISP is binding. Yet, within its own portfolio a BRP should be free to dispatch assets following its own strategy to balance the portfolio. For this reason, the delivered T-prognosis can not be used as the ultimate reference of what the asset is going to produce. Besides, as the initial T-prognosis is delivered at 15.15 D-1 for each hour of the next day, there is still a large uncertainty in this T-prognosis especially for the last hours of the next day. In case an asset owner overestimates its production during the redispatch period and delivers a higher T-prognosis than the actual possible production. Than it will be actioned based on this overestimated production, it does not have to curtail its production at all but gets payed for downward capacity it does not deliver. As there is no incentive to deliver a correct T-prognosis, parties could in that case anticipate on congestion and strategically deliver a higher T-prognosis. A second problem is that because there is no incentive to deliver a correct T-prognosis, the quality of these prognoses especially for smaller assets is extremely bad. Assets do not invest any time to deliver a good quality forecast and simply deliver D-7 exchange or always the same load. For those reasons, using the T-prognosis as a reference is currently not a viable option.

As discussed above, transaction costs can be a barrier for assets to offer capacity as an ancillary service (Williamson, 2010). Therefore, it seems important to have a verification method which does not involve extra transaction costs for smaller assets which offer redispatch capacity. A new data stream for each individual wind assets seems therefore not viable for small scale assets. Besides, this also involves a lot of costs for the grid operators as they need to organize setting up all these individual data stream with each of the wind assets. In addition, as the amount of redispatch actions and the amount of assets delivering actions will increase, the workload for the grid operator to verify all these redispatch actions will increase significantly. Consequently, the method for verification should become uniform and automated.

Thus, the design requirements for the proposed method are;

- A method which uses existing data streams in order to avoid transaction costs for both the grid operator and the TSP
- A method which is uniform and can be applied on all type of wind assets; individual wind turbines, clusters of wind turbines, offshore windfarms and onshore windfarms.
- A method which can be automated, in order to avoid that each individual redispatch action has to be verified manually by the grid operators

4.2 Process of redispatch action

Before proposing the method for verification, it is necessary to gain insight into how the process of a downward redispatch action for wind in the Dutch control area works. The process is visualized in Figure 15. Before 15.15h D-1, the owner of the wind asset is obliged to deliver a T-prognosis for each ISP of the next day. In practice, this means that the asset owner needs to deliver a prognosis of what will be consumed or generated on this specific grid connection for each 15 minutes during the next day. In order to deliver this prognosis, the asset owner will use the power curve of the wind asset and the weather forecast to deliver an individual transport prognosis for each of the requested time periods. All these T-prognoses together with the T-prognoses of all other grid connections, will then be used by the grid operator as input for the network security analysis.

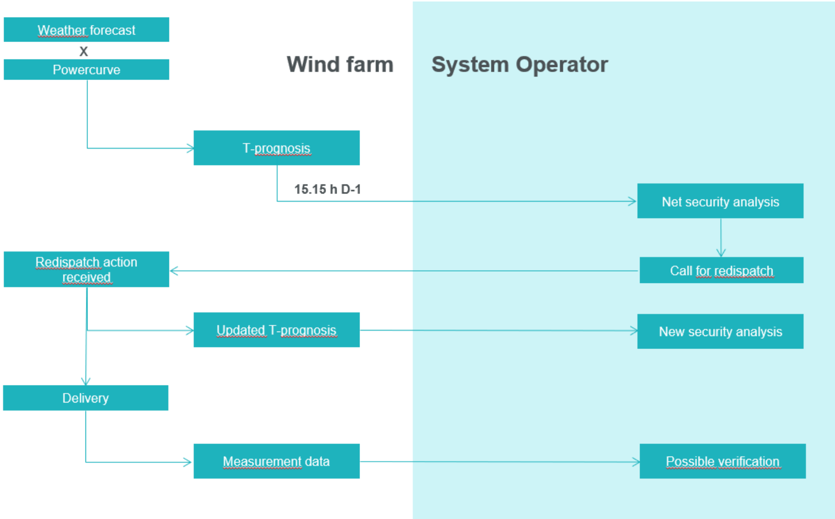

Figure 15: The process of a downward redispatch action delivered by a wind asset

This network security analysis will calculate the loads on the whole electricity network for each individual ISP. When the calculated load on (individual) parts of the network exceeds the safety limits, this indicates possible congestion within the network. This congestion can be solved using redispatch actioned based on the bids made in RESIN or GOPACS. In order to get extra liquidity in the market, the grid operators will publicize a message to the market which entails the need for upward and downward capacity in the specific congestion area along with the related time period. In this way, the market parties are able to offer extra upward or downward capacity via RESIN or GOPACS during the right time periods. As wind assets operate with zero marginal costs they will always offer their full expected production on the day-ahead market and will therefore only make bids for downward redispatch.

The grid operator will then select the most cost efficient bids to solve the congestion problem. In case the bids on both platforms do not fulfil the needed amount of capacity in both directions, the grid operator can manually call the operators of certain assets to deliver extra capacity. If the wind asset has made a bid for downward redispatch and this bid or a part of this bit is actioned by the grid operator. The operator of the wind asset will receive a requested amount of redispatch. They then need to update their T-prognosis which includes the redispatch amount. This updated T-prognosis will then again be used by the grid operator to make a new network security analysis to verify if the congestion problem is solved or more redispatch is needed.

Next, the asset will deliver the redispatch during the requested time period. Afterwards, the measurement data will be send to the grid operator by the party with metering responsibility. This measurement data can then be used in order to verify the delivery.

4.2 Modelling the Active Available Power of the windfarm

Although the measurement data of the asset (grid connection) becomes available and can be used for verification, as discussed in *Chapter 2: Verification of the delivered AS*, a baseline is needed in order to determine whether the asset was actually curtailed or not. Based on these design requirements and the existing AAP method, the idea is to create an algorithm which can calculate the amount of curtailment by using the existing measurement data stream and publicly available local weather conditions. The algorithm should be able to calculate the available power production for each wind asset given the local weather conditions. This maximum possible power production (or Active Available Power) can then be compared with the actual production to find the curtailed amount. This comparison can be done ex-post after the measurement data is received by the TSO. The moment of comparison is visualized in Figure 16.

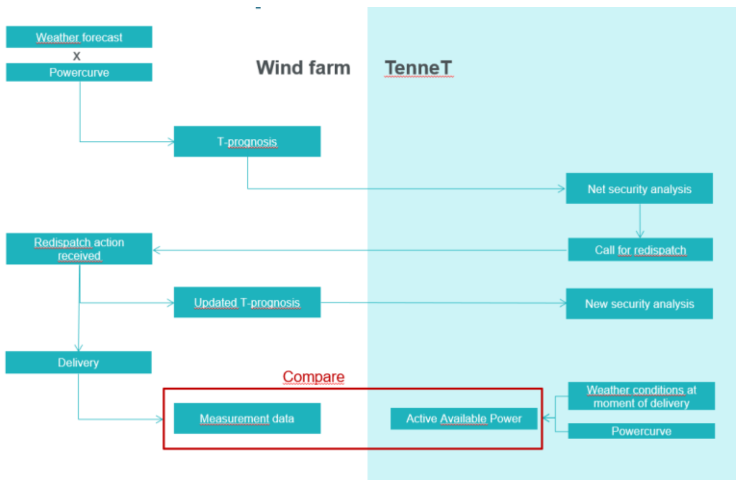

Figure 16: Generate the active available power of the wind asset by data-drive power curve and the local weather conditions at the moment of delivery.

As some literature suggests, a method to calculate the possible production of wind assets is to use the theoretical power curves of the installed wind turbines and the windspeed at this location (Kusiak et al., 2009b; Lydia et al., 2014). A disadvantage is that the theoretical power curve of each installed turbine is needed for this method. In order to model the distributed small wind assets, this requires a comprehensive database which registers the power curve of each installed wind turbine. Whereas the performance of a wind turbine declines with age, the theoretical power curve is only representative of the production during the first period of operation (Staffell & Green, 2014). Moreover, Janssens et al. (2016) argue that while a theoretical power curve model does only take one parameter(windspeed) as input, there are also other phenomena which influence the power curve like shading effects, wind fields and turbulent air. "A theoretical model does not consider these complicated interactions. Nevertheless, it is possible to take these into account by using data-driven approaches wherein a power curve is constructed directly from the data instead of using the underlying physics. By using a data-driven methodology no explanation or origin is linked directly to certain phenomena. A model is created based on measurements, hence the phenomena present in the data are encompassed in the model. For example, if due to the wind field the turbine underperforms at high wind speeds, a data-driven model will take this into account because this phenomenon is manifested in the data. By being able to take the phenomena which are present in the data into account, a more accurate power prediction is possible" (p. 332).

Using such a data-driven model can be applied to model the output of single turbines but also for wind parks as a whole. Wan et al. (2010) show that such a method can be used to estimate the generation output of an entire wind park. In that case the data-driven model does only require the historical power output of the wind asset as a wole (exchange of the grid connection) and the local weather conditions. This also avoids having a comprehensive database which has to register a power curve or other characteristics for each individual wind asset. Even information concerning the amount of wind turbines behind the grid connection is not necessary.

While the grid operators have access to measurement data on their grids, the historical power output data of the individual wind assets is already available to them. In the second place, the local historical weather conditions can be obtained via various publicly available datasets. The quality of these historical weather grids has improved significantly during the last decades (Boehme & Wallace, 2008; González-Aparicio et al., 2017). Staffell & Green (2014), state that reanalyses are used in several different studies as a wind speed data source. Meteorological reanalysis is a method which provides a picture of the weather of the past as close to reality as possible. It combines local weather observations (e.g. satellite images or observation of weather stations) with weather models to provide a consistent picture of the past weather at a local level. Comparison of the European ERA-40 reanalysis by Kiss et al. (2009) with two nacelle measurements in Hungary showed 'surprisingly good' agreement. Furthermore, Kubik et al. (2012) used the global NASA reanalysis to estimate the total generation of wind parks in Northern Ireland on an half-hourly basis which appeared to be more accurate than using local met mast data. Olauson & Bergkvist (2015) have used the MERRA reanalysis data to model the total hourly Swedish wind power production. When comparing this data to the data from the Swedish TSO, the mean absolute error(MAE) in hourly energy was 2.9% and the root mean squared error(RMSE) was 3.8%.

In 2017, the Dutch Offshore Wind Atlas(DOWA) was launched which is a 2.5 by 2.5 km grid with historical wind data covering the Netherlands(TNO, 2020). The DOWA is based on a combination of the weather models HARMONIE and ERA5. The model is validated against satellite measurements, meteorological mast and LiDAR measurements (KNMI, 2020). This validation shows an average wind speed deviation of 0.1 m/s with actual measurements. Besides the DOWA seems to show a very good representation of the daily rhythm (TNO, 2019).

The method proposed is to model a data-driven power curve for each individual wind asset which uses the historical power output of the individual asset and the local historical weather conditions based on the DOWA. Using this data-driven power curve and the weather conditions at the moment of redispatch, the AAP can be calculated for the relevant time period.

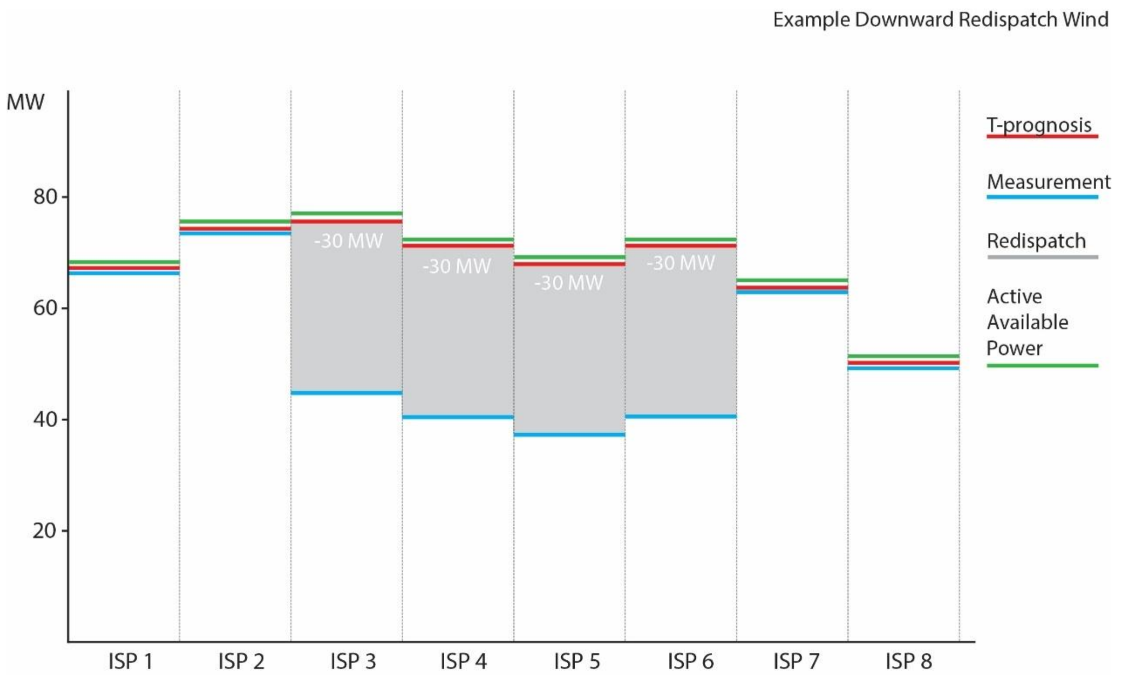

Figure 17: AAP method during a perfect down regulation

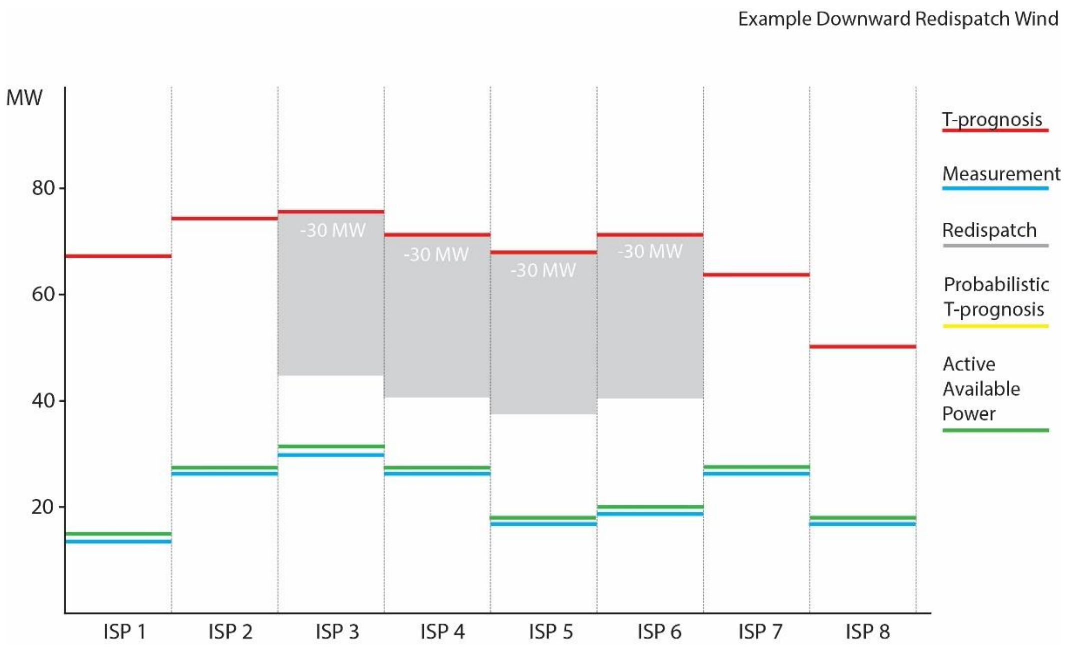

Figure 18: AAP method during a non-delivery

4.2 Evaluating the quality of the delivered T-prognosis

Whereas the above proposed method does only assess whether actual curtailment happened, it can also be useful to evaluate the quality of the submitted T-prognoses of the wind assets. Explicitly as this T-prognosis forms the input for network security analysis and therewith the cause of the actioned redispatch. Therefore the effectiveness of the actioned redispatch depends on the quality of the T-prognosis. As parties do not have an incentive to deliver accurate T-prognoses, it can be the case that the assets owner out of ease deliver wrong T-prognoses. What can happen is that they for example deliver D-1 instead of an accurate forecasted prognosis. Another issue is when asset owners deliberately deliver a higher T-prognosis .

In both cases, forecasted congestion is solved by redispatch while in reality the congestion does not have to occur as the prognosis was simply off. Hirth & Schlecht (2019) have identified that within zonal electricity markets with market-based redispatch, parties are incentivised to foresee what will happen in the redispatch market and use this foresight to bid strategically on the day-ahead market in order to extract extra profits. They will increase their planned production within the congested areas and at the same time make bids for downward redispatch. As the area is congested, they will then be payed to downregulate their production for high redispatch prices. This strategy is the so-called increase-decrease gaming . Secondly, the forecast uncertainty of a wind asset can also be reason to deliberately deliver a higher T-prognosis than weather forecast suggests. When redispatch is actioned in a congested area, a market restriction can be imposed on this area. As described in *Chapter* 1.1.1 Remedial action process, in case of downward redispatch, the market restriction entails that all parties within the congested area cannot produce more than indicated by their T-prognosis. In case a wind asset owner underestimates the power production for a certain hour and a market restriction is imposed, this implies that the asset owner needs to curtail its production to the last delivered T-prognosis. For this reason it might be strategical for asset owners in congestion areas to incorporate the uncertainty of the weather by always delivering higher T-prognoses than is actually forecasted.

However, within the network security analysis this extra forecasted energy can lead to redispatch actions which redispatch energy which would have never been produced in the first place. Accordingly, this leads to unnecessary costs for the grid operator and therewith the electricity user.

For the above reasons, it is can be useful for the grid operator to benchmark the quality of the submitted T-prognoses of wind assets which offer redispatch capacity. When the prognosis lacks quality or has a disproportionally large bias, this can be addressed to the asset owner.

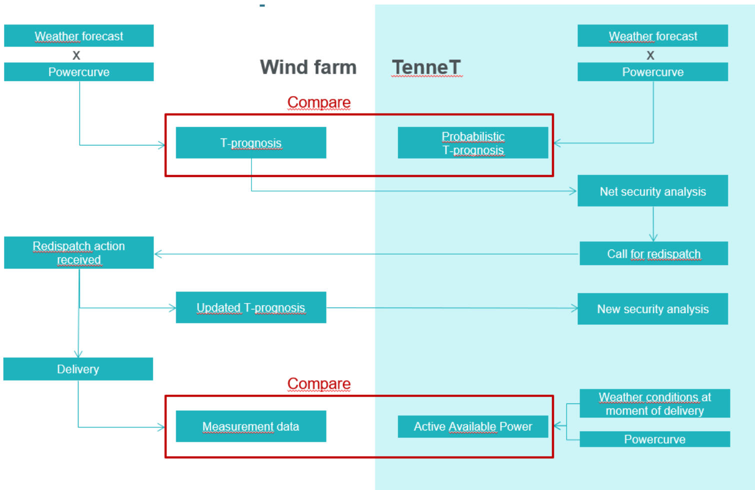

Figure 19: Process of redispatch action with the evaluation of the T-prognosis.

In order to benchmark the delivered T-prognoses, it is proposed to generate an own forecast using the weather forecast at the delivery moment of the T-prognoses(15.15 D-1) on the location of the asset and the derived power curve for the specific asset. Ideally, the weather forecast is an ensemble-based probabilistic forecast, while in that case it incorporates the uncertainty of the weather forecast. An ensemble-based probabilistic weather forecast is a probabilistic representation of the distribution of an ensemble of runs of the weather model as illustrated in Figure 20. In this way a confidence interval can be created in which the delivered T-prognosis is allowed.

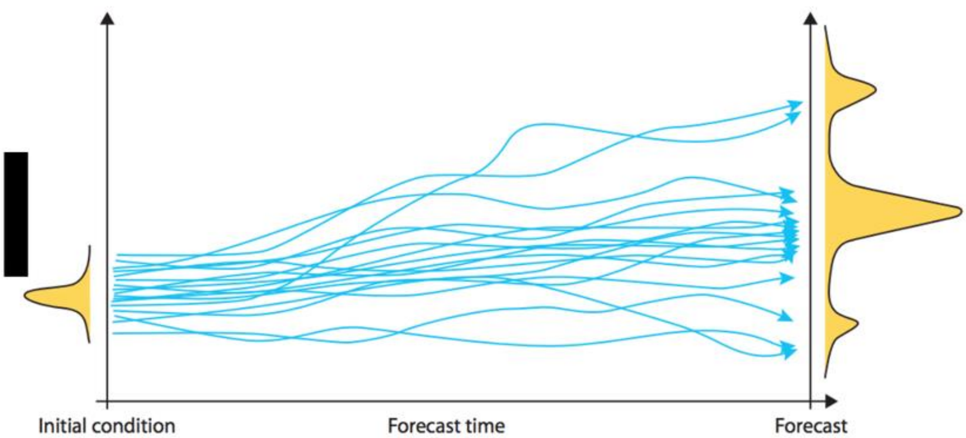

Figure 20: The principle on an ensemble based probabilistic forecast. The yellow areas represent the probability distribution of the forecasted outcome. The blue lines represent the individual runs of the model (Kuster, 2015).

In order to test this method, the KNMI HARMONIE historical forecast dataset was purchased by TenneT. This dataset consisted daily historical forecasts from 2015 till 2019 totalling up to 8.5 terabyte of data. Unfortunately, due to delays, the corona crisis and the extensive time necessary to upload the dataset on the server I was unable to receive the right pieces of the datasets in time. Accordingly, it was not possible to test the performance of a probabilistic T-prognosis.

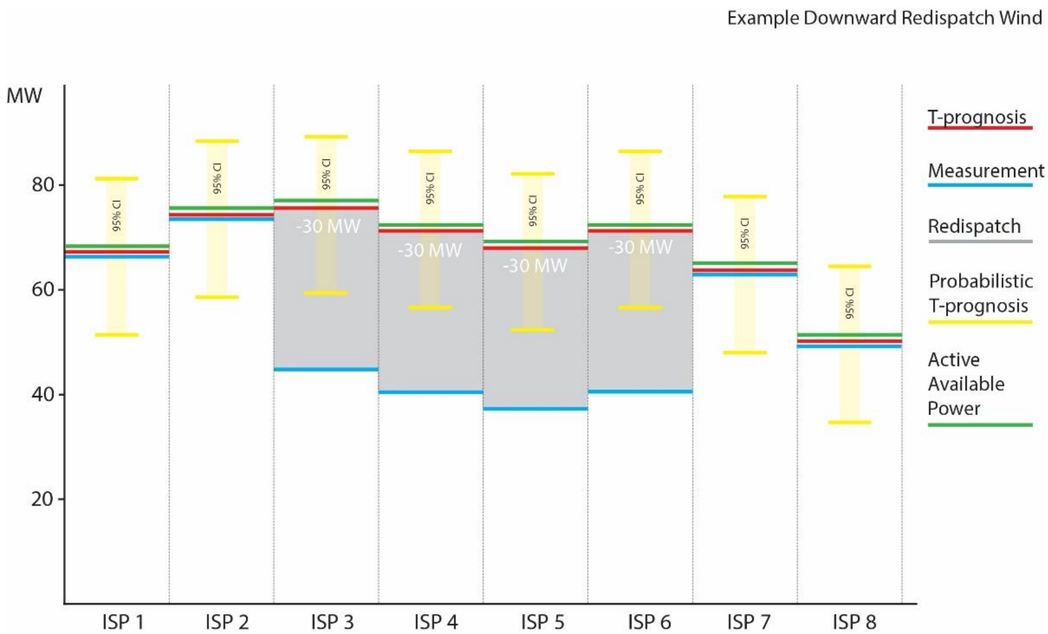

Figure 21: Probabilistic T-prognosis method during a perfect down regulation

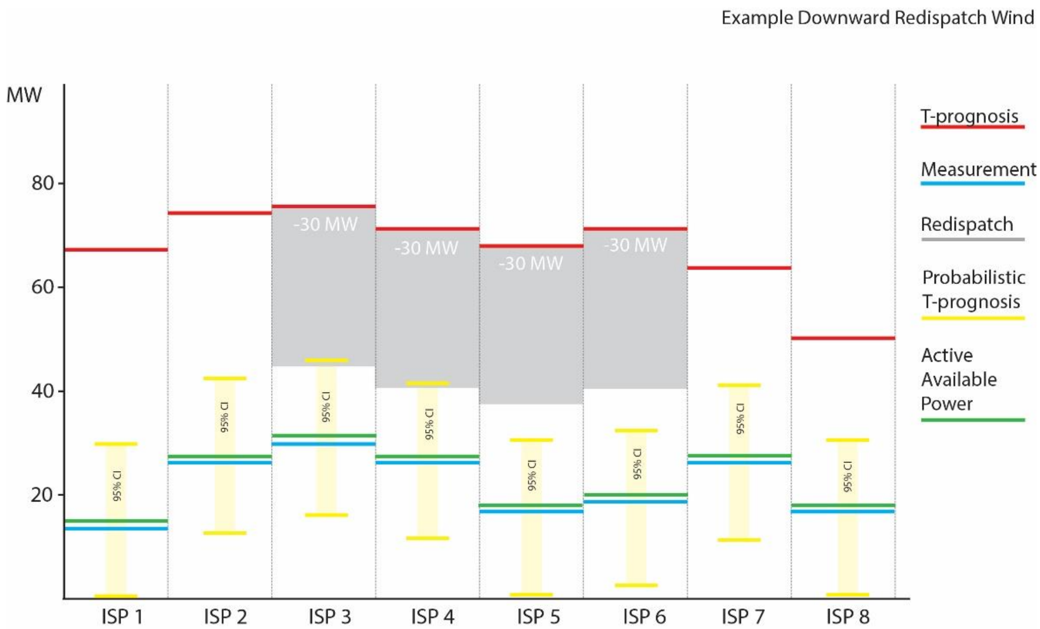

Figure 22: Probabilistic T-prognosis method during a non-delivery

Chapter 5: Testing the method

In order to test the proposed method, five windfarms connected to the HV grid were selected. The reason to select only wind assets on the high voltage(HV) grid is that TenneT only has production data available of assets connect to the HV grid. The selected windfarms are Gemini(offshore), Luchtterduinen(offshore), Noordzeewind(OWEZ)(offshore), Prinses Amalia Windpark(PAWP)(offshore) and Westermeerwind(onshore). The specification of the parks can be observed in Table 10: Specifications of the five selected windfarms below. The model is tested on an hourly time interval for all five parks and for 2 of the parks on a 10 minute time interval.

Windpark	Hub Height(m)	Amount of wind turbines	Installed capacity(MW)	Coordinates middle of park	Time interval
Westermeerwind	95	48	144		**Hourly**
Gemini	89	150	600	54.036 N, 5.9630 E	Hourly
Luchtterduin	81	43	129	52.416 N, 4.1666 E	Hourly,
Noordzeewind(OWEZ)	70	36	108	52.606 N, 4.419 E	Hourly, 10-min
Prinses Amalia windpark(PAWP)	60	60	120	52.589 N, 4.206 E	Hourly, 10-min

Table 10: Specifications of the five selected windfarms

5.1 Data

5.1.1 Production data

In order to test the model, for all five windfarms, hourly production data was collected for the period of July 2016 up to and including 2018. The E66 measurement data corresponding to the EAN of the windfarm was used and aggregated on a hourly time interval. The E66 measurements are validated measurements which are also used for settlement. In order to also test the model on a 10 minute time scale, the EMS Scada of the TenneT grid data of the park Luchterduinen, Noordzeewind(OWEZ) and Prinses Amalia Windpark(PAWP) was collected on a 10 minute time interval for the year 2017. The EMS Scada data is unvalidated measurement data from the TenneT SCADA system.

5.1.1 Historical weather data

In order to model the AAP of the windfarms, the historical weather conditions of the farm on the location of the farm are required. To attain the historical weather conditions on the locations of the windfarms, the Dutch Offshore Wind Atlas(DOWA) was used. This dataset covers a period of 11 years from 2008 until and including 2018 with historical wind data. The domain entails the whole of the Netherlands including the North Sea area east and north of the Netherlands where the Dutch offshore wind parks are located. The whole domain can be observed in *Appendix A*. The data contains hourly information of wind conditions on a 2.5 by 2.5 km grid spacing on different height levels up to 600 meters (DOWA, 2020). All five selected windfarms are located within this grid, this dataset is therefore used to model the production on an hourly basis for the period of July 2016 up to and including 2018. For the offshore wind regions Borselle, Hollandse Kust Noord(HKN) and Hollandse Kust Zuid(HKZ), a Large Eddie Simulation(LES) has been performed which results in a dataset with a higher time resolution of 10 minutes (the areas are indicated in Appendix B). As the parks Prinses Amalia Windpark(PAWP) and Noordzeewind(OWEZ) fall within HKN and Luchterduinen falls within the HKZ area, these three parks can be modelled on a 10 minute time interval. The LES simulation is only performed for 2017 on these relevant locations, for this reason only 2017 can be modelled on the 10 minute time interval.

5.2 Data preparation

5.1 Preparation of dataset for modelling Active Available Power

In order to match the production data of each windfarm with the wind conditions on the location of this same windfarm, the DOWA wind data of the grid point which is closest to the coordinates off the middle of the windfarm was used. From this dataset, all variables were selected on 10, 100, 150 and 600 meters height. This data was then joined with the production data on the corresponding timestamp. This creates the final dataset containing all necessary data to model with. Below all the included variables are listed. Production is the outcome variable in the modelling while all other listed variables are the predictor variables.

- Production in kW
- Wind speed in m/s at 4 height levels
- Wind direction in 360 degrees at 4 height levels
- Air pressure in Pascal at 4 height levels
- Air temperature in Kelvin at 4 height levels
- Relative humidity in Percentage at 4 height levels

Before modelling, the dataset was preprocessed and cleaned.

5.1.1 Indicating Un-availability

Similar to conventional power plants, windfarms experience maintenance, unplanned outages, HV-switching activities and power trips. Some new wind turbines also have bird and bat control systems which switch the turbine off when birds and bats are too close to the turbine (Kleyheeg-Hartman et al., 2018). In the future the forecasting models which forecast bird migration can also indicate moments when wind turbines at specific locations need to be switched off (Parisé & Walker, 2017; Speksnijder, 2018).

During these occurrences, the park is not able operate at all, or only able to operate on a certain percentage of its full capacity. For example when a certain amount of wind turbines needs maintenance, the park can only produce with the other wind turbines and is therefore not able to reach its full capacity. As this model proposes to model the possible power of the park based on its installed capacity, these moments of unavailability should not be intergraded into the model. According to European legislation, when generators have experience an unavailability of 100MW or more, they should publicize this unavailability (Commission Regulation (EU) No 543/2013 of 14, 2013). In the Netherlands by reason of its large amount of installed capacity, only Gemini needs to publicize its hours of unavailability (GEMINI, 2019). Hence, these moments were incorporated into the dataset and indicated as ‘Un-Available’. In this way, these moments can be excluded for training the model. For the other parks, visual inspection of the production profile and related weather conditions was performed in order to filter the obvious cases where the modelled expected production largely deviates from the actual production.

Inspecting the production data of the different windfarms, it was observed that there were a reasonable amount of timepoints where the production was negative. This can be explained by the fact that large wind turbines do use energy to operate. Among the functions which consume electricity are; the yaw mechanism (this mechanism holds the blades at the right angle relative to the wind direction to extract maximum energy from the wind), blade-pitch control, lights, controllers, communication, sensors, metering and heating of the blades(to avoid icing) (Rosenbloom, 2006). Besides, electricity consumption can also occur because of maintenance. While this electricity consumption is not related to the wind conditions, it ought not be accounted for in the model. For this reason, all negative production has been set to zero.

Next, for reasons of data protection, all data needs to be made anonymous. Therefore, the output of all the windfarms has been normalized between 0 and 1. In this way, the output of the farm is always expressed as a percentage of the installed capacity.

5.2 Feature transformation

As windspeed is the main driver of the power output of wind assets, it can be regarded as the most important weather variable for determining the power output (Janssens et al., 2016). For this reason it is highly important to catch the right relationship between the power output and the windspeed. A power curve expresses the relationship between the wind speed and the power generation of an individual turbine as can be seen in Figure 23.

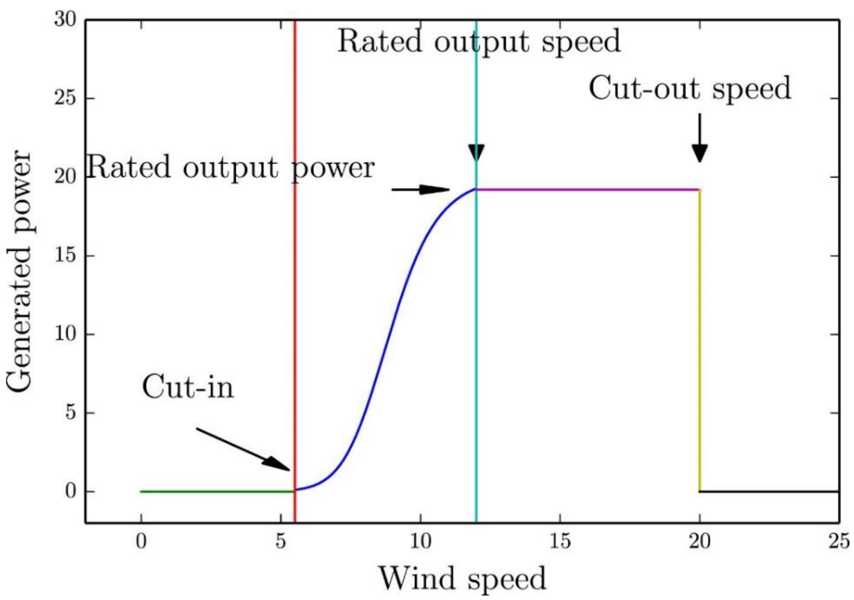

Figure 23: Example of a wind turbine power curve (Janssens et al., 2016)

The objective of a power curve is to estimate the power production of a wind turbine in standard operational conditions. The power curve shows how the power generation of an individual wind turbine diverges over different wind speeds. During low wind speeds the wind turbine will have insufficient torque to overcome friction and therefore not be able to produce electricity. This cut-in windspeed is generally somewhere around 3.5 m/s. Also during vastly high windspeeds the wind turbines are do not produce electricity as they can be damaged when operating during extreme wind conditions. This cut-out speed is generally around 25 m/s. When the wind exceeds the cut-in speed, the generation output increases quickly. Yet, around the rated output speed, the power output reaches a maximum level. This is the maximum level at which the electrical generator can still work (Neill & Hashemi, 2018).

A theoretical power curve between this cut-in speed and the rated output speed uses the air density, the windspeed, the swept rotor area and power coefficient to determine the power output (Janssens et al., 2016). As the air density and windspeed are variables which change over time, this information can be taken into account into the model. Davis (2014), argues that wind speed can be adjusted by the atmospheric density to catch the relationship between the two. As the rotor blades get pushed by moving air which has a certain density, the energy transferred to the rotors is larger when the air gets more dense. For this reason the energy transferred to the blades is a combination of windspeed and air density. The International Electrotechnical Commission (IEC) has a standard process for taking this into account. The equation for the adjustment can be observed in Eq.(1) below.

$$\boldsymbol{U}_{\text{norm}} = \boldsymbol{U} \cdot \left(\frac{\boldsymbol{\rho}}{\boldsymbol{\rho_0}}\right)^{\frac{1}{3}} \tag{1}$$

where U_{norm} is the adjusted wind speed, U represents the measured wind speed, ρ indicates the air density and ρ_0 indicates the standard atmospheric density which is considered (1.225 kg/m3).

While the dataset contains Air Pressure(**P**), Air Temperature(**ta**) and Relative Humidity(**hur**), Air Density(ρ) can be calculated using the model of International Standard Atmosphere(ISA). This generated air pressure was then used to transform the windspeed variable to the adjusted wind speed($\boldsymbol{U_{norm}}$) using the formula above. As the relationship between the windspeed and the power output does not tent be linear but has a cubic relationship, some variables have been added in order for the model to catch this relationship (Jung & Broadwater, 2014). The adjusted windspeed is squared and cubed, resulting in the variables adjusted windspeed squared ($\boldsymbol{U_{norm}^2}$) and adjusted windspeed cubed ($\boldsymbol{U_{norm}^3}$).

Nonetheless, a power curve is affected by more than only wind speed and air density. According to Janssens et al. (2016) “Other phenomena also influence the power curve such as the wind field, yaw and pitch misalignment, shading effects by nearby obstacles, turbulent air created by turbines nearby and the mechanical behavior of the turbines” (p.332). As the power curve of a windfarm or a set of wind turbines as a whole can be explained as an aggregation of individual power curves, these effects also influence this curve. Below, in Figure 24 the power curve of one of the modelled wind parks can be observed.

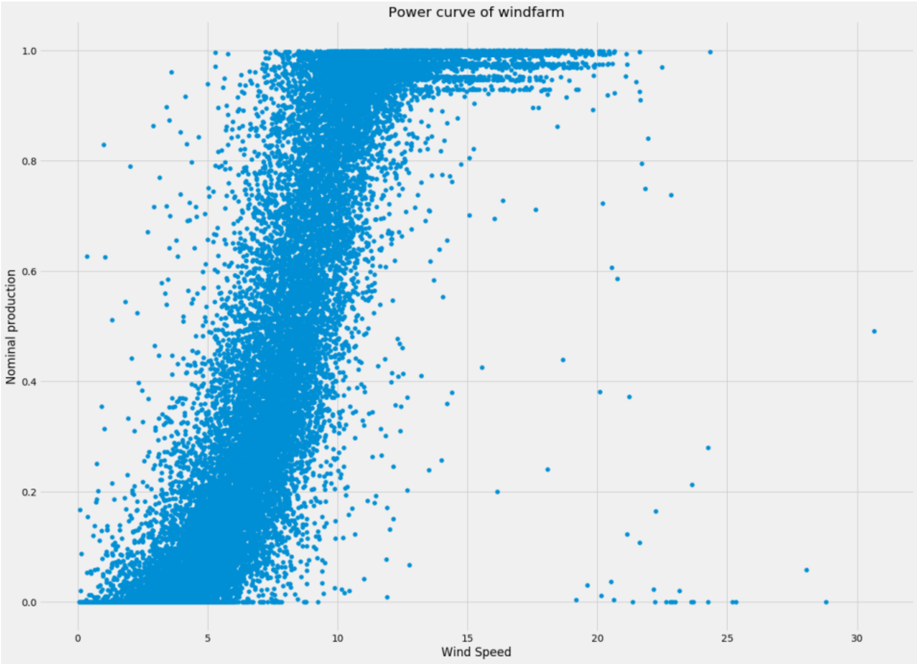

Figure 24: Power curve of one of the wind farms which shows the relation between the windspeed and the nominal production of the park.

It becomes evident that the power curve is not a thin line but rather a cloud of observations which are quite dispersed. This inclines that with similar wind speeds, the park can have different levels of output. While within a windfarm the turbines are located close to one another, the effects that Janssens et al. (2016) talks about are even more dominant within a windfarm than for an individual windmill. The most important one is the wake effect(also called shading effect). This effect should always be taken into account when modelling a windfarm (González-Longatt et al., 2012). While a wind turbine generates energy from the wind it catches, it takes away this energy from the wind. Therefore the wind leaving the turbine has a lower energy content as the wind which enters the wind turbine in the front. The wind turbine will for this reason create a wind shade in the downwind direction as can be observed in the figure below.

Figure 25: The wake effect behind turbines which is revealed by fog at Horns Rev wind farm in Denmark (*Recharge*, n.d.).

This is called a wake, which is trail of wind that is turbulent and slowed down. Although wind parks place the wind turbines at least a minimum distance away from each other to prevent that there is excessive turbulent air nearby the downstream wind turbines, the wind speed is still decreased and thus there is an effect on the generation of the downstream wind turbines (Pusz, 2001). The wind farm layout has a significant effect on the generation output and when the wind direction changes the output of the park as a whole changes due to changing shading effects (Yang et al., 2019). The effect is visualized clearly in Figure 26 below. In this figure a windfarm is visualized from above under two different wind directions.

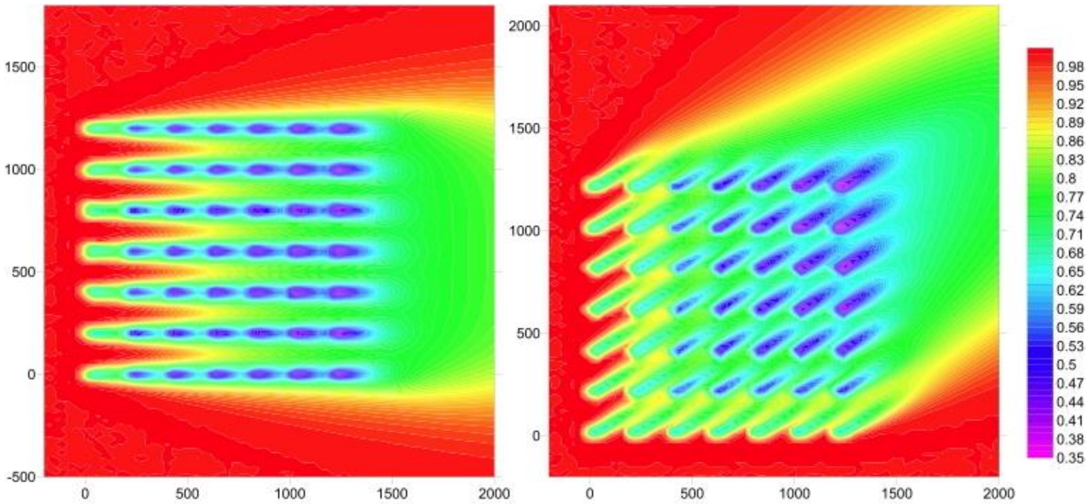

Figure 26: Normalized total wind speed contours at hub height for wind directions 270(left) and 240(right) degrees (CERC, 2011).

Exploring this dataset also showed different power outputs with different wind directions. Below two scatterplots are shown in which the first represents the power curve for the observations that have a wind direction between 135 and 180 degrees. While the second figure shows a the power curve for the observations which have a wind direction between 315 and 360 degrees.

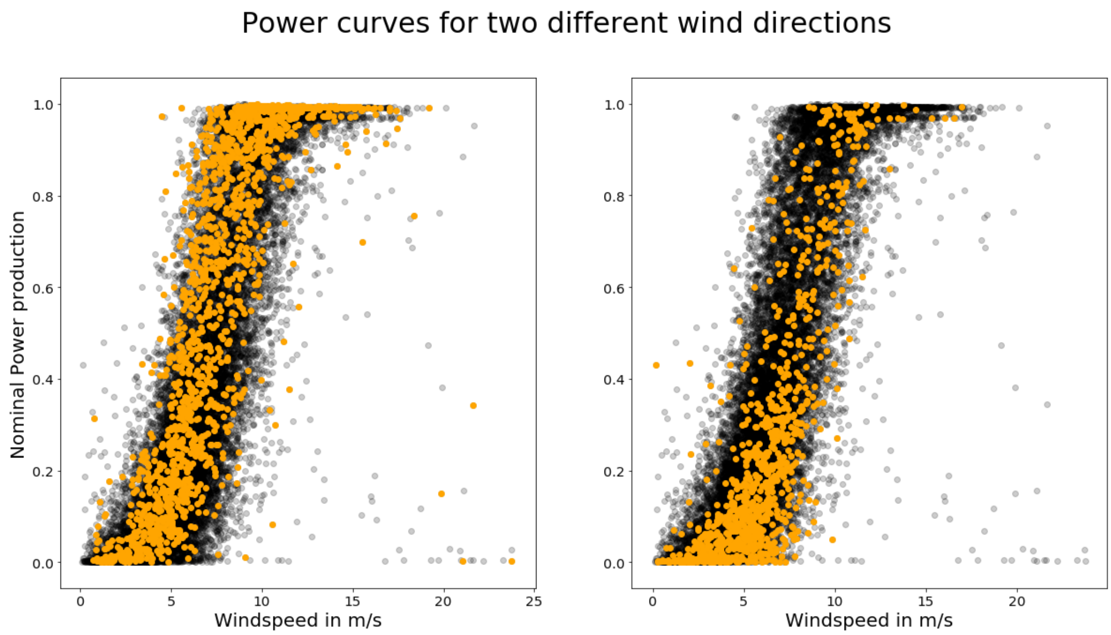

Figure 27: Scatterplots of power production by windspeed for two different wind directions. On the left all observations with a wind direction between 225 and 270 degrees are plotted and on the right with a wind direction between 315 and 360 degrees.

It becomes clear that the observations with a wind direction between 225 and 270 degrees have on average a higher power output during the same windspeeds than the observations with a wind direction between 315 and 360 degrees. In order to include these effects into the model, the wind directions was divided into eight buckets of 45 degrees. For each of these eight buckets, dummy variables were created to indicate if the observation is within this wind direction bucket **(Udir)**.

Furthermore, wind turbine operation is also influenced by wind gradient. As vertical windspeeds can differ, the blades close to the ground level will experience a different windspeed compared to the blades on the top. This results in an asymmetric load and can have an effect on the generation output of a wind turbine (Li et al., 2018). In order to include the effects of the different vertical windspeeds, a new variable named vertical windspeed difference**(δU),** was created which contains the difference between the windspeed at 20 meter and the windspeed at 150 meter. The values within the new variable are then divided in four buckets and from these four buckets dummy variables were created.

The characteristics of the underlying process which is trying to be modelled may vary with time. In other words, the power generation of the wind turbines can differ over time under the same weather conditions. This non-stationarity can be related to different aspects including seasonal changes but also physical changes to the wind turbines like damage or dirty blades. In order to take along this non-stationarity into the model, dummy variables for year, month and hour have been created.

5.3 Modeling techniques

Within this project three different algorithms were employed to model the power output of the windfarms: OLS linear regression, K-nearest neighbors regression(KNN) and Extreme Gradient Boosting(XGBoost). This section gives a summary of these algorithms.

5.3.1 Linear regression(OLS)

At first a simple parametric model was investigated, namely, linear regression. The model assumes a linear relationship between the wind conditions and the generation output of the park. The model assigns weights to all the individual variables (which are deducted from the wind conditions) which add up to the eventual estimated generation. As the windspeed has a cubic relation with the power output, the squared and cubed variables enable the linear model to catch this cubic relationship. The model can be described by Eq.(2) as below:

$$\widehat{Y_t} = \beta_0 + \beta_1 U_t + \beta_2 U_t^2 + \beta_3 U_t^3 + \beta_4 P_t + \beta_5 hur_t + \beta_6 ta_t + \beta_7 Udir_t + \beta_8 \delta \mathrm{U}_t \qquad (2)$$

where $\hat{Y}$ is the predicted production at time *t*, *U* is the adjusted wind speed at time t, U^2 is the adjusted wind speed squared at time t, U^3 is the adjusted wind speed cubed at time t, *P* is the pressure at time t, *hur* indicates the relative humidity at time t, *ta* represents the average temperature at time t, *Udir* is a dummy variable indicating the buckets with the different wind directions at time t, δU represents the difference in windspeeds between 10 meters and 600 meters at time t. Al variables are included at the four different heights: 10, 100, 150 and 600 meters.

5.3.2 K-nearest neighbors regression(KNN)

Literature suggests that KNN can be good method for modeling the output of wind assets (Janssens et al., 2016; Kusiak et al., 2009; Fischer et al., 2017). The algorithm will evaluate new observations to observations which are remembered from the training phase. In order to calculate the target value of a new observation, the algorithm takes the average of the target values of the *k* closest neighbors in the training data. In order to calculate the power generation of the windfarm $\hat{Y}$ at time *t*, the algorithm computes the mean power generation over the k-nearest neighbors in the feature space at time *t*. The nearest neighbors are determined by calculating the Euclidean distance of the variables of the neighbors and the variables from the observation at time *t* (Fix & Hodges, 1989). In this way the model will include specific complex relationships between the wind conditions and the generation output as takes the average over observations with similar wind conditions. As the model is non-linear, it can detect linear but also non-linear relationship. The model is also very easy to apply as the number of *k* is the only parameter which needs to be optimized. However, as the model takes the average of the nearest neighbors it is quite sensitive to outliers. The rule is given by the equation:

$$\widehat{Y_t} = \frac{1}{k} \sum_{j=1}^{k} Y_{(j)} \qquad (3)$$

Where $Y_{(j)}$ represents the power generation of the park linked to the j-th nearest neighbor of the observation you want to estimate at time *t* (Fix & Hodges, 1989). The number of *k* of neighbors is optimized using a for loop testing the error for each k using 10-fold cross validation on the dataset of one of the parks where the optimal *k* was set at 49. This same number of *k* was used over all the different parks.

5.3.3 XGBoost Regression

XGBoost or eXtreme Gradient Boosting, is an algorithm which is dominating machine learning competitions recently and also proven to be successful in wind power forecasting (Demolli et al., 2019a). It was designed in order to increase speed, performance and also scalability relative to the gradient boosted decision trees which it relates to (Brownlee, 2019). The XGBoost algorithm has the intention to minimize the objective function by building better decision trees. An advantage of using this model is that it does not require assumptions regarding the distribution of the underlying data. As it is also a non-linear model, it is able to catch both linear as non-linear relations in the data. The model is tree based and will split the data in different parts to find specific relationships, eventually it will combine a different amount of trees to one model. In this way it can catch more complex relationships compared to the linear regression which simply applies one model to the entire dataset. The algorithm uses boosting which means that it will build the new trees on the training data which was not well estimated and contained larger errors. In this way the model can is able to improve itself by capitalizing the large errors to build a new stronger model. Therewith tree based models have proven to be successful in wind power forecasting (Foley et al., 2012). The XGBoost regression algorithm can be formulated as done by Demolli et al. (2019) in the Eq.(4) below.

$$F_{obj}(\theta) = L(\theta) + \Omega(\theta) \text{ where } L(\theta) = l(\hat{y_i}, y_i) \text{ and } \Omega(\theta) = \gamma T + \frac{1}{2}\lambda|w|^2 \qquad (4)$$

where $F_{obj}(\theta)$ is the objective function, $L(\theta)$ represents the loss function between predicted production $\widehat{Y_t}$ and the actual production Y_t, $\Omega(\theta)$ corresponds to the regularization term, γ is the learning rate, T is the amount of leaves in the tree, λ represents the regularization parameter and w represents the weights related to the leaves in the tree.

In this research the parameters where selected using scikit-learn preprocessing tool of random grid search (scikit-learn, 2019). The parameters where then optimized using the 10-fold cross validation on the dataset of one of the parks. The parameters were initialized once and the same parameters were used over all the parks. The used parameters are: number of estimators=75, subsample=0.8, learning rate=0.1, maximum depth of a tree=4 , subsample ratio of columns=0.85. All other parameters where left on the default values.

5.3 Testing

With the purpose of testing the performance of the different models, the method of *k*-fold cross-validation was applied. Using this method, the original dataset is randomly divided into *k* subsets with similar size. From these subsets, one of the subsets is reserved as the test set which is used to test the model performance. The other (*k*-1) subsets are than utilized to train the model. This cross-validation procedure is than reiterated *k* times. In this way each *k* subset will be used precisely one time as test set. Therewith, all the observations are used for training as well as testing and every observation is then used for testing once. The metrics applied for evaluating the performance of the model on the testing data can then be averaged of the *k* iterations to produce a general estimation of the model performance on the full dataset. Although *k* is not a fixed parameter, 10-fold cross-validation is most commonly used (McLachlan et al., 2004). For this reason, to test the performance of the different models in this research also 10-fold cross-validation was applied.

Chapter 6: Results

Within this chapter the accuracy of the different models on the different parks is presented. For each of the parks 10-fold cross-validation was applied to test the different models on all the available data of the parks. To judge the performance, three metrics are calculated: r-squared(R^2) which is shown in Eq.(5), mean absolute error(MAE) which is shown in Eq.(6) and root mean squared error(RMSE) which is shown in Eq.(7).

$$R^2 = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y})^2} \qquad (5)$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{j=1}^{n} |y_i - y_i| \qquad (6)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y}_i)^2} \qquad (7)$$

where $\hat{Y}$ is the predicted production of the park and Y is the actual production of the park.

While all the data has already been normalized to make the data anonymous, the MAE and the RMSE are relative to the installed capacity. These metrics will be used in the tables below.

6.1 Active Available Power algorithm

The AAP method was tested using linear regression, k-nearest neighbors and XGboost with different time scales and weather data inputs.

6.1.1 Results for the DOWA modelled on a hourly time interval

The DOWA data on the location of the windfarms was used with all variables at the heights 10, 100, 150 and 600 meters as input for the hourly time interval. In

	Linear Regression			**KNN(49)**			**XGBoost**		
	R2	**MAE**	**RMSE**	**R2**	**MAE**	**RMSE**	**R2**	**MAE**	**RMSE**
Wind park 1	0,89	7,66	10,79	0,84	8,91	12,98	0,90	7,03	10,3
Wind park 2	0,90	7,78	10,9	0,90	7,27	10,89	0,91	6,98	10,32
Wind park 3	0,89	7,94	11,62	0,89	7,67	11,96	0,90	7,23	11,11
Wind park 4	0,85	7,38	9,82	0,82	7,73	10,88	0,88	6,37	8,79
Wind park 5	0,89	7,43	10,63	0,88	7,28	11,17	0,90	6,75	10,11
Average	**0,89**	**7,64**	**10,75**	**0,87**	**7,77**	**11,58**	**0,90**	**6,87**	**10,13**

Table 11 the results for all individual parks and the average over all parks can be observed. The names of the parks have been anonymized for this public version of the report.

	Linear Regression	**KNN(49)**	**XGBoost**

	R2	MAE	RMSE	R2	MAE	RMSE	R2	MAE	RMSE
Wind park 1	0,89	7,66	10,79	0,84	8,91	12,98	0,90	7,03	10,3
Wind park 2	0,90	7,78	10,9	0,90	7,27	10,89	0,91	6,98	10,32
Wind park 3	0,89	7,94	11,62	0,89	7,67	11,96	0,90	7,23	11,11
Wind park 4	0,85	7,38	9,82	0,82	7,73	10,88	0,88	6,37	8,79
Wind park 5	0,89	7,43	10,63	0,88	7,28	11,17	0,90	6,75	10,11
Average	**0,89**	**7,64**	**10,75**	**0,87**	**7,77**	**11,58**	**0,90**	**6,87**	**10,13**

Table 11: Results of the different models on a hourly time interval using 10-fold cross validation

Regarding the R^2, MAE and RMSE, XGBoost is the best performing model across all wind parks. Linear Regression performs slightly worse with less explained variance(lower R^2 values) and larger errors. The KNN regression with 49 nearest neighbors has the worst performance based on all three metrics. The explained variance(R^2) seems to be very comparable over all the different parks which indicates that the model does not seem to overfit on one specific park. For Gemini the explained variance is slightly higher for all models. This could be explained by the fact that the unavailability of this park is published and could be filtered out of the model training and testing. Another noticeable point is that for the park *Wind park 4*, the explained variance is lowest but the MAE and RMSE are also lowest. This could be explained by the fact that the park undergoes degradation of the output over the years of observation. In order to calculate the MAE and RMSE the largest output of the parks during the entire observation period was taken as the installed capacity. As for *Wind park 4*, the performance decreased over time one can argue that the installed capacity also decreased over time. For this reason the errors made later in the observation period are relatively smaller compared to the installed capacity.

6.1.2 Results for the DOWA modelled on a 10-minute time interval

In order to test the model also an a 10 minute time interval, the EMS SCADA data of the TenneT substations on a 10 minute time interval was used. It should be regarded that this data is unvalidated and can therefore be less accurate than the validated E66 measurements. For the park Luchterduinen the EMS SCADA contained errors and was regarded as invalid. For this reason Luchterduinen was excluded from the 10 minute analysis. The DOWA LES reanalysis modelled on a 10-minute time interval was used as input data. As the reanalysis has only been performed on these two locations for 2017, the period which was modelled and tested upon only consists the year 2017 alone. In Table 12 the results from the different models on a 10-minute time interval can be observed over the two different parks. The XGBoost model does also in this case outperform the other models on all three metrics. Surprisingly, the KNN model performs better compared to the linear regression. Over all models, the accuracy of the predictions decreased substantially compared to the hourly time interval.

	Linear Regression			KNN(49)			XGBoost		
	R2	MAE	RMSE	R2	MAE	RMSE	R2	MAE	RMSE
Windpark 1	0,82	8,89	12,08	0,82	8,54	12,00	0,82	8,49	11,94
Windpark 2	0,85	9,07	12,95	0,84	8,85	13,33	0,85	8,48	12,71
Average	**0,83**	**8,98**	**12,52**	**0,83**	**8,70**	**12,67**	**0,84**	**8,49**	**12,33**

Table 12: Results of the different models on a 10-minute time interval using 10-fold cross validation

6.1.3 GEMINI modelled with weather station and ERA5

The performance of the models based on the hourly DOWA weather input can also be compared to the performance of the models with actual weather measurements as input data. For the Gemini wind park the wind data of the weather station on the helipad is used as input data. The weather station data is collected at 10 meter height and had two extra variables namely *highest windspeed per hour* and *average windspeed during the lasts 10 minutes.* Results are presented in Table 13, the modeling is done with and without these extra variables to give a fair comparison with the DOWA input models. With the weather station data as input, again the XGBoost algorithm has the best performance on all three metrics and therewith indicates to be the best model. The actual weather station data proves to be more accurate over the DOWA model with and without the extra variables, despite the fact that the wind condition are only measured on 10 meters height. This indicates that there must be a deviation within the DOWA from the real measured wind data. Which is also explainable while it is a reanalysis.

The DOWA reanalysis data is only available form the next year which is problematic for settlement. Therefor the performance of the ERA5 reanalysis is also tested while this one is published within 5 days of real time. While the DOWA is a combination of the HARMONIE and ERA5 models and is also validated against satellite measurements, mereological masts and LiDAR measurements, it is expected that is would outperform the ERA5 dataset. The results show that the DOWA input does indeed outperforms the ERA5 input in on all three metrics.

	Linear Regression			**KNN(49)**			**XGBoost**		
	R^2	**MAE**	**RMSE**	**R2**	**MAE**	**RMSE**	**R2**	**MAE**	**RMSE**
Gemini(Weather Station same var.)	0,906	7,56	10,75	0,893	7,68	11,45	0,926	6,36	9,49
Gemini(Weather Station extra var.)	0,913	7,32	10,33	0,893	7,68	11,45	0,933	6,01	9,03
Gemini(ERA 5)	0,881	8,55	12,06	0,879	7,92	12,09	0,883	7,81	11,95
Gemini(DOWA)	0,903	7,78	10,9	0,903	7,27	10,89	0,913	6,98	10,32

Table 13: Results of the different models on an hourly time interval based on the weather station data of the Gemini helipad using 10-fold cross validation

6.1.4 Distribution of errors

The distribution of the errors by different windspeeds is visualized in Figure 28 for one of the wind parks. Similar distributions were observed at the other parks. The figure shows that both positive as negative errors have an approximately normal distribution. It demonstrates that the inaccuracy is most substantial for wind speeds between 5 and 12 m/s. This is also the area in the power curve where the output of a turbine is most sensitive to wind speed (as in Figure 24). For lower and higher windspeeds, the model is more accurate in predicting the output. This is an important insight and can be used to communicate an uncertainty based on the wind conditions. As Wang et al. (2019) suggest, the 'probabilistic power curve model' or the 'error-based probabilistic model' can be used for this. Furthermore, although the negative and positive errors have a similar distribution, the negative distribution tends to be centered a bit more to the right compared to the positive one. This suggests that the model is more likely to overestimate the production during lower wind speeds and underestimate the production during higher wind speeds. The distribution of errors seems to perfectly match the research of Kubik et al. (2013).

Another important observation related to this distribution can also be made. While the distributions of the negative and positive errors almost mirror each other, the arithmetic mean over the whole observation will be close to zero. In other words, on the long term the negative and positive errors will arithmetically cancel each other out. When you would try to estimate the capacity factor over a whole year, this would therefore be very close reality. When summing the total output of the AAP model over 2 years of production at Gemini, this estimated production only deviates from the actual measurement by 0.026%. Yet, when estimating the power generation on an hourly time interval only the magnitude of errors is considered and not the sign of the errors. This also explains why the absolute error on an 10-minute time interval is smaller than the error on an hourly time interval. Simply because the modelling errors of the wind conditions will cancel each other out over a longer time span.

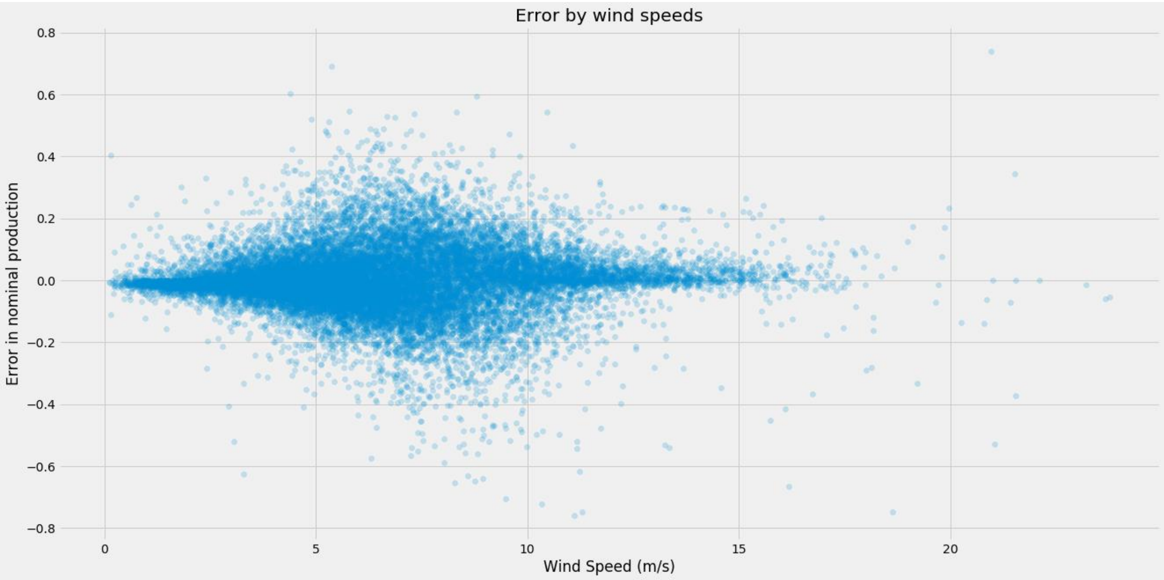

Figure 28: Distribution of errors by different wind speeds for DOWA input data on an hourly time interval

6.1.5 Testing the AAP method on actual cases

As the last part of the chapter explains the performance of the AAP method on the moments where no curtailment of the park occurred. The method serves the purpose of estimating the AAP during moments of curtailment. In order to evaluate the performance of the model during curtailment, the method was tested on actual redispatch actions. All actions are limited to one of the parks. As the information is commercially sensitive all data is anonymized and the time of the occurrences is deleted. The maximum redispatch amount in terms of installed capacity was only 3.33%. Therefore, in terms of installed capacity, the actioned redispatch was smaller than the error of the model. For that reason it would not be expected that the model is able to identify cases very accurately. In total 13 redispatch actions have been examined. During four of these actions the model seems to identify the redispatch action very accurately. These cases can normally be observed in the appendix, however for this public version of the report they are not included. Four other actions were partly well identified but also for some time the model partly underestimated the output of the park. During these moments curtailment can be partly observed. During five other redispatch actions, the model underestimated the output during the entire redispatch period. As a wind park can never produce more than the available power, it is clear that when the model underestimates the production, this can only be due to the error of the model. Thus, during these moments, it can be regarded that the method failed. Two important remarks should be made regarding these actions. First, these actions have never been verified in any way, therefore it is uncertain if the actioned capacity was actually curtailed. Although the method clearly shows curtailment in some of the cases, it is not sure that actual curtailment occurred during all of the moments. The last remarks is that for all the actioned capacity de expected curtailment was smaller than the uncertainty of the model.

Chapter 7: Summary, Conclusion and Discussion

This chapter provides a summary of the objectives, methodology and results of this research. Next, the main conclusions are discussed grounded on the insights gained within this research.

7.1 Summary

Due to the changing energy landscape in which more and more electricity is produced by renewable electricity sources, a rising demand for AS is expected. As the conventional providers of AS capacity get phased out, renewable energy producers like solar and wind need to take over the supply of these services. Related to the intermittent, variable and weather dependent output of renewables, the existing methods to correctly verify the delivery of actioned AS capacity can not be applied for these assets. TSOs are now exploring how to update these methods in order to allow future participation of alternative AS capacity. As wind energy is the main source of renewable generation in the Netherlands, this research focussed on getting more insight into how to improve verification concerning ancillary services delivered by wind asset.

In order to improve verification methods of AS, a thorough understanding of how AS function is required. The first chapter explains what AS are and what role they play in maintaining the integrity and stability of the electricity system. Two main categories of AS are examined namely; congestion management and balancing services. All individual markets related to these two main categories are explained. The related contracting method, bidding process, method of activation, financial settlement and other specifications of the different products are defined. Thereafter in the next chapter, the relevance of verifying the delivery of ancillary services is discussed. For each of the individual products it describes whether or not there is a verification process. For the balancing products, the current methods are explained. However, no verification occurs for the redispatch products. While the total costs for redispatch increases and the assets delivering redispatch capacity get smaller and more distributed, the relevance of verifying whether the actioned redispatch was actually delivered on the right location increases. And so, a need for verification of actioned redispatch was identified. In Chapter 3 the current and future role of wind assets in delivering AS is described. It demonstrates the technical capabilities of wind assets to deliver AS products and discusses the existing AAP method which can be used for verification. Although, this method seems to be accurate and suitable for verification, it requires setting up new data streams with the wind assets who provide the AS in order to get the SCADA data. Collecting all this data from the individual assets incurs transaction costs for both the grid operator as the asset owner. Whereas TenneT wants to open up the redispatch market for smaller distributed assets, it want to keep the barriers to enter the redispatch market low. Moreover, the work and costs it entails for TenneT to collect and process all the data of these individual assets is undesirable.

This exposed the need for a verification method for the delivery of redispatch by wind assets which using the existing data streams. Concerning the large amount of individual wind assets, the method should also be able to be automated and be uniform(applicable to different types of wind turbine).Taking these design requirements into account, in Chapter 4, the existing AAP methodology which uses SCADA data of the wind turbine as input was transformed to a data-driven AAP methodology using reanalysis data as input. The data-driven approach makes the method uniform and applicable regardless of the type of wind asset. The method simply learns from the relation between the wind conditions and the output of the asset based on historical data without needing asset specific information. Furthermore, by using a reanalysis as input, only the coordinates of the asset need to be known to determine the historical wind conditions at the location of the asset. The location of an asset is included in the EAN registration of a grid connection and is therefore known by the grid operator. In this way, no new data stream between the grid operator and the asset owner is required in order to exchange the SCADA data of the turbines. Moreover, the method can use the information of the redispatch action together with the observed difference between the calculated AAP and the actual output of the asset to automatically verify if both correspond.

This method was tested on five large wind parks in The Netherlands using the historical production data and the DOWA reanalysis. Three models were compared, including linear regression, k-nearest neighbors and XGBoost. The performance of the models was then estimated using 10-fold cross validation. For all individual parks the XGBoost algorithm outperformed linear regression and k-nearest neighbors in terms of accuracy. It demonstrated to be able to estimate the output of the parks on an hourly basis reasonably well with an average MAE of 6.87% over the five parks. When comparing the DOWA reanalysis data as input with the data of an actual weather station as input, the latter showed only to be slightly more accurate. The performance decreased to an average MAE of 8.49% over the two parks modelled on a 10 minute time interval. Based on the production data of Gemini, the DOWA reanalysis was compared to the ERA5 reanalysis which is available within 5 days of real time. The DOWA reanalysis slightly outperformed the ERA5 reanalysis in terms of accuracy. At last, the XGBoost algorithm was tested on all 13 actual redispatch actions which occurred within the timespan of the available dataset. In four cases the model identified curtailment very clearly, at four cases the model partly identified curtailment and at five cases the model underestimated the production during the redispatch period.

7.2 Conclusion

The goal of this research was to give an answer to the main research question:

“To what extent can verification methods be updated in order to improve verification concerning ancillary services delivered by wind asset?”

Within this research a clear need for an appropriate verification method suitable for verifying the delivery of redispatch by wind assets was recognized. The research targeted to examine to what extent the existing AAP method could be updated in order to become suitable to verify a large amount of distributed assets. It can be concluded that the proposed data driven AAP method using reanalysis data as input is under no circumstances as accurate as the methods using the SCADA data of the wind turbines. However, the model still seems to be able to give a reasonable estimation of the output of the different parks on an hourly time interval especially during low and high wind speeds. Another finding is that the model has poorer performance on a shorter time interval related to errors which arithmetically average out over longer time periods. Whilst most redispatch actions get actioned in hourly blocks, the accuracy on an hourly basis does seem to give a decent representation. When testing the method on actual redispatch actions, the model seemed to be only partly able to identify curtailment during redispatch actions which comprise small shares of the installed capacity. Nevertheless, it is expected that actioned amounts will generally become larger shares of the installed capacity, especially with smaller assets. During these types of actions the model will be more capable of identifying the curtailment. Overall, it can be concluded that the verification method for redispatch delivered by wind assets can be updated using existing data streams. This will result in an improved performance compared to the non-existent method. The method does not seem to be accurate enough to use for actual settlement. It seems that the method can rather be used qualitatively in a way that the asset owner will be confronted with the results of the model when it identifies non delivery.

7. Discussion & Recommendations

This chapter discusses the methodology and results in more depth. It also raises the limitations related to the research. At last recommendation for further study are presented.

7.1 Discussion

To the best of my knowledge there is no public scientific literature which tries to model the Active Available Power(AAP) of individual windfarms using public metrological reanalysis data. On the one hand, there are plenty of public studies which focus on modelling the output of individual wind farms based on the SCADA data of the park or nearby measurement towers (ELIA, 2015; Göçmen et al., 2019; Malte Jansen et al., 2014; Janssens et al., 2016; M. L. Kubik et al., 2013; Wan et al., 2010; Wang et al., 2019). On the other hand, public metrological data has been used within several studies for modelling total wind power generation within certain regions (M. Kubik et al., 2012; Olauson & Bergkvist, 2015). However, none of the available literature uses public metrological data to estimate the production of individual wind farms on a short time interval. Therefore, this research contributes to the understanding of how accurate public metrological reanalysis data can be for estimating the power output of individual windfarms. These insights can be useful for grid operators to estimate the AAP of wind assets when having no access to SCADA data.

It should be noted that the AAP model based on the DOWA dataset is nowhere near as accurate as the AAP induced from SCADA data in predicting the output during periods of normal operation. Jansen et al. (2014) reports a RMSE of 2.14% on a 10-minute time interval based on SCADA data while the DOWA model has an average RMSE of 12.33% on this same time interval. Nevertheless, this comparison can be regarded as unfair when regarding it as a method for estimating available power during down regulation. Generating the AAP from SCADA data suffers from severe limitations during down regulation as it sums the wind speeds of all the individual anemometers on the wind turbines which are affected by the curtailment. Göçmen et al. (2019) report that: "the sum of those individual signals is a clear overestimation of the available power of a down-regulated wind farm; simply because the wind speed is higher at the downstream turbine location(s) due to the decrease in wake losses under curtailment" (p. 206). As the reanalysis data represents a free stream of the wind speeds, the model is not influence by this overestimation (KNMI, 2018). It can therefore be assumed that the accuracy during normal operation of a wind farm is the same as during curtailment. When using an algorithm which corrects for these effects by taking the upstream anemometers, they report a standard deviation in terms of error (which they regard as the uncertainty of their model) of 10.5% for Thanet wind farm and 5.3% for Horns-Rev-I wind farm on a 5-minute averaged evaluation. The standard deviation in terms of error reported in this research is 12.1% for WPEZ and 12.7% for PAWP on a 10-minute time interval.

A large part of the fact that there is more uncertainty within the AAP modelled using the DOWA over the AAP which is modelled using SCADA data can be explained to the fact that the DOWA is a modelled representation of the actual wind conditions. Especially on shorter time intervals it is hard to model the actual wind condition at a specific location. Therefore, there is already an uncertainty in the wind conditions which are used as input for the model. Contrarily, the models induced from SCADA data use the actual measured wind conditions. But as numerical weather prediction has become a lot more accurate in recent history and is expected reanalysis will become even more accurate in the future, therefore this uncertainty related to the model is expected to decrease (Bauer et al., 2015).

Yet, this does not explain all the error as for Gemini, the actual wind conditions have been used as input. Another aspect which therefore seems to be important are the horizontal differences in wind conditions over the outlay of the parks. The actual weather station data was only measured at one single point in the park. Also the input for the DOWA model takes only the grid point in the middle of the windfarm as a reference. But as Gemini has a surface of 68km^2, the wind conditions can differ on one side of the park compared to the other side of the park. These differences are not integrated in both the DOWA as the weather station model. When using the windspeed data of individual turbines these different horizontal wind conditions do get included. Furthermore, the modelling in this research also lacked the information regarding the amount of wind turbines which were online. When there are one, two or even more wind turbine not operational, this model still considers the park to be operating at full capacity. This means that both the training and the evaluation of the model happens on an incorrectly estimated capacity. Conroy et al. (2011) argue that turbine manufacturers indicate that wind turbines have an average availability of 97% in terms of time. For this reason, it is expected that in wind parks modelled within this research, some turbines will be offline during a considerable period of time. Although the unavailability of Gemini is integrated, this unavailability only considers periods when a large share of the capacity is unavailable. It does not consider moments where just a few turbines are offline and does also not comprise the information regarding the amount of wind turbines which are online. When using the SCADA data, the data of each individual turbine it is also provides how many turbines are operational.

Next to the unavailability of some of the turbines or other large unavailability of the park, it is also possible that the parks actively steer the parks to balance their own portfolio or that it reacts on very high imbalance prices. This also decreases the model accuracy similar as when a certain amount of turbines are offline. However, the parks receive a subsidy for all the electricity produced during the first 15 years. When they would curtail, they would lose this subsidy for the curtailed share of their production. Currently the subsidies are 158 euro/MWh for OWEZ, 163 euro/MWh for PAWP, 169 euro/MWh for Gemini and 181 euro/MWh for Luchterduinen (VEMW, 2018). As they do not want to lose these subsidies, it is expected that they would only curtail to balance their own portfolio during extreme imbalance prices. The moments with extreme imbalance prices of more than 100 euro/MWh where excluded to see if the model performance increased. However, there was no improvement of the model performance observed.

It is noteworthy that the accuracy of the AAP model for Gemini with the weather station data as input seems to correspond closely with the research of Wan et al. (2010). They model the output of a wind park based on two measurement towers. Using a Neural Network they achieved a MAE of 6.1%.

Even if the AAP modelled based on SCADA data is a lot more accurate, it also has also some disadvantages. As Wan et al. (2010) argue; “direct measurement of wind speed at each turbine is impractical, and it is extremely demanding in terms of modelling effort and computational resource to forecast the wind speed at each turbine” (p. 17). It also requires a data connection between the grid operator and the wind asset which is costly. Such a connection between the asset requires new ICT infrastructure, extra work for the asset owners to deliver the SCADA data and a lot of effort for the grid operator to collect and process all this data. It is also the question who does the modelling of the AAP in case the SCADA data is send to the grid operators. Does the grid operator have to model the AAP for each wind asset individually based on the SCADA data or do the asset owner have to model their own AAP and deliver this to the grid operator. Therefore collecting this data from the individual assets incurs transaction costs for both the grid operator as the asset owner.

Although current redispatch actions are in practice still mostly actioned in blocks of hours, they are officially registered and settled on a 15 minute time interval. Having a model which can handle the 15-minute time scale is therefore important. Due to the unavailability of DOWA on a 15-minute time scale, the results reported in this research on a 10-minute time scale give the closest representation of how accurate a model with metrological reanalysis input can be for the 15-minute time interval. As it was observed that the models get more accurate when they model for longer time periods, it can be expected that the results on a 15 minute time interval will be a bit more accurate compared to the 10-minute time intervals.

An important limitation of the performed analysis is that the method is only tested on larger windfarms. It is unknown how accurate the method will be on individual wind turbines or smaller sets of wind turbines. One assumption is that complex farm specific processes like shading effects and turbulent air created by nearby turbines will decrease and therefore the model can become more accurate. Conversely, Jansen & Speckmann (2013) suggest that determination of possible feed-in will become more precise with an increasing number of wind turbines per park due to compensating effects. It is also the case that when one off the wind turbines is offline in a large park, this results in a small difference between the generated power and available power of the park. But when one turbine is offline in a small set of turbines, this results in a large difference between the generated power and the available power of this set of turbines. When there is no information in how many turbines are online, the model will be trained with data containing errors in representing the active power of the asset. The larger these errors, the worse this model will represent the real active available power of a park.

The XGBoost algorithm can be regarded as the best model to estimate the AAP from all the tested methods. It should be noted that the parameters for XGBoost have been optimized using the Scikit-learn function ‘Random Grid Search’, the chosen parameters are the best random combination of the values indicated on a pre specified grid. Doing a full grid search could pick the optimal parameters but is too computationally intensive for a personal computer. This could improve the model accuracy slightly. Furthermore, the XGBoost model seems to generalize well over all parks once the parameters are optimized for one. It must be stressed that although the XGBoost model performs best, it is also the most computationally expensive method of the three models considered.

When the AAP method would be used in practice, it is important that the verification can be done within a limited time frame. The big limitation of the DOWA is that it becomes only available at the end of each year. The ERA5, despite of the weaker performance would therefore be the only viable reanalysis which can be used as weather input data in actual operation as it becomes available within 5 days of real time.

A limitation to the data driven approach is that it needs historical data to learn from. For this reason, when the asset is new and has no previous output data, the model does not have enough observations to learn from and will therefore have a very weak performance. Furthermore, the model is also not suited for a wind asset which has a battery pack behind its connection point to store electricity. When the is no information of when the battery is charged and uncharged, this will trigger an error in training the model. The same shortcoming relates to connections which employ wind and solar on one grid connection(also called cable pooling). In this case it is unknown which share of the output is related to the solar panel and which share of the output is related to the wind turbines.

In general it can be discussed whether having market parties deliver forecasts for the expected production (T-prognosis) of renewables is very efficient. As there is not yet a good incentive to deliver a correct forecast, a lot of market parties deliver a forecast which has bad quality or lacks quality at all. While the network security analysis is based on these forecasts, the bad quality of these forecasts can lead to unnecessary actioning of redispatch or transportation problems when discovering the forecast errors too late. As conventional plants are steerable in terms of output, only the asset owner knows how much it will produce or consume. However, renewables are fully weather dependent and their output can be forecasted relatively simple based on the weather forecast. At this moment the share of renewables in the Dutch electricity grid is still rather low. Yet, when this share increases, the forecasting errors related to these renewables will also increase. This will incur extra redispatch costs or unexpected transportation problems. In that case, it might be more efficient to have a national forecasting team at the TSO which forecasts all the input of renewables assets and anticipate on redispatch problems based on their own forecasts. In that way it can simply use its own forecast as a reference for actioning redispatch. In this way the asset can only produce up to a certain output. This also makes the whole validation process much more simple as the grid operator only needs to check if the asset did not produce more than the indicated production. However, this goes against the idea that the market is most efficient in providing its own forecasts. Therewith, it brings along extensive changes to the current operations and creates uneven ground between renewables and conventional units.

Another solution to improve the whole process is to have a financial incentive related to the quality of your production forecasts. For example a penalty if you production forecast deviates to a unrealistic amount. However, law and regulations should in that case be changed as it goes against the idea of freedom of dispatch. It would restrict BRPs from balancing their own portfolios by adjusting the output or consumption of individual assets. Accordingly, this could also lead to extra imbalance causing problems for the TSO.

8.2 Recommendations

In order to get a good representation of how the actual model could work which will be used in daily operations, it is important to get more insight in the performance of the model with the ERA5 reanalysis as input. Accordingly, the model using this as input should be tested on all the five wind parks. Overall, more effort could be made to optimize the performance of the model by trying different methods of feature transformation. Also different modelling approaches could further improve the accuracy of the method. Recurrent neural networks, support vector machines and random forests would be recommended models to test as they have recently shown success related to wind power forecasting (Demolli et al., 2019b; Manero et al., 2018). Furthermore, within this research only one grid point from the reanalysis was used as input for the wind conditions. It is recommended to test whether the model performance improves when feeding all grid points inside or surrounding the area of the park into the model. Within this research the AAP is presented as a deterministic value. Nevertheless, as discussed in the results section, the uncertainty of the model is not the same during all wind conditions. During windspeeds up to 5 m/s and above 10 m/s the errors of the model are lower compared to moments when the windspeeds fall within this range. It would therefore be useful for the user to present a probabilistic representation of the estimated AAP to indicate how certain the AAP calculation is. This can be done running an ensemble of the XGBoost model. Most importantly, while it is uncertain if the method has a similar performance on small scale assets, the model should be tested on individual wind turbines and smaller sets of wind turbines. Likewise, the method was now only tested on actual redispatch actions comprising very small shares of the installed capacity. It would therefore be recommended to test the method on future occurrences which action a larger share of the installed capacity. At last, the method as applied for wind assets could be developed in a similar way for solar plants. A data-driven model can be deduced from the production data of solar plants together with the solar radiation deduced from the ERA5 reanalysis or satellite images.

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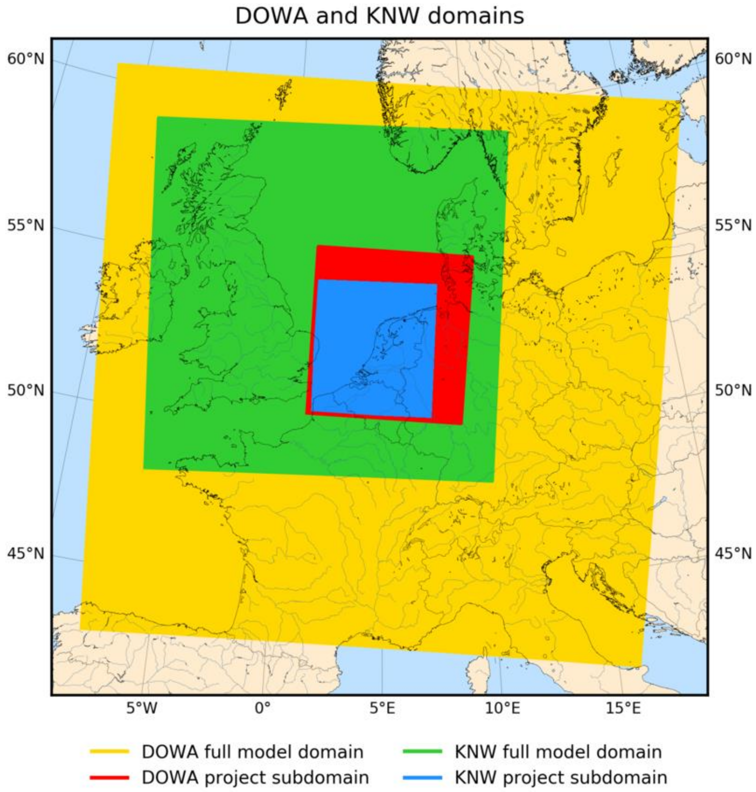
Appendices

Appendix A: Full DOWA Domain



Appendix B: LES Areas