Methods for optimization of a German TSO's electricity market performance with special attention to wind power

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Abstract

The topic of this thesis is devoted to the search of the methods to optimize a TSO's (Transmission System Operator) market performance. The position of a TSO as a market player is a quite new one, since its traditional obligations consist in ensuring of network availability, congestion prevention and management, ensuring the system stability. It is emerged from the pursuit of German government of reducing the dependency of national energy system on energy imports and environmental and climate protection. In these circumstances a TSO was obliged to assume all the energy produced by renewable energy sources (RES) to bid it further on the energy market. Thereby it is faced with the special characteristics of this "market product": due to the significant share of stochastic wind power in the assumed energy mix the reliability of its trading operations becomes risky. In order to bring the wind power feed-in a TSO receives in line with the regulations of German energy market (i.e. to bid them as an unlimited order[1]) it must have a trustworthy day-ahead forecast. German TSOs use by their operation the weighted average of several wind power forecast tools developed in the recent years (i.e. by energy & meteo systems GmbH, EuroWind GmbH, IWES). The majority of them is based on numerical weather predictions models and provides the information how much wind power can be expected at each point of time. Thus they announce the variations in the electricity production of wind farms in advance and largely reduce the degree of randomness attributed to wind energy. However there are still deviations to be observed between the day-ahead forecast and wind power feed-in really occurring. These deviations result in significant costs (billions euro) both for TSOs (i.e. for provision and application of control energy) and end-customers (increased electricity tariffs due to additional costs of TSOs for equalisation of forecast errors). The reasonable measure to countervail these problems is the improvement of the day-ahead forecast a TSO receives as a service. Respectively the research community occupied with the search of the adequate solutions is rather meaningful. However, a TSO as a recipient of a day-ahead forecast does not have any possibility to influence the potential sources of forecast inaccuracy. It needs therefore a solution that could optimize its day-ahead market operation regarding the limited information resources it has: the weighted day-ahead wind power forecast it receives as a service and the real-time values of wind power feed-in that it is given in 24-hours-delay. This consideration turns the current research topic into the rather novel one. Two alternative methods to solve the mentioned problem are proposed: Q-Learning and Kalman filter. Their performance is tested within the simulated model of German equalisation scheme for RES and verified with the real-life data of wind energy feed-in. Achieved results are evaluated with the common accepted error measures.

[1] Hour contract without a specification of a price

Kurzfassung

Diese Dissertation beschäftigt sich mit dem Thema der Optimierung des Marktverhaltens eines ÜNB (Übertragungsnetzbetreiber). Dabei ist die Position eines Marktteilnehmers relativ neu für den ÜNB. Traditionell sind die ÜNBs die Dienstleistungsunternehmen, welche die Infrastruktur der überregionalen Stromnetze zur elektrischen Energieübertragung operativ betreiben, für bedarfsgerechte Instandhaltung und Dimensionierung sorgen und Stromhändlern/-lieferanten diskriminierungsfrei Zugang zu diesen Netzen gewähren. Die neue Position des Marktteilnehmers entstand erst in den letzten Jahren infolge des Strebens der deutschen Regierung, die Abhängigkeit des nationalen Energiesystems von den Energieimporten zu reduzieren und dieses umweltfreundlicher zu gestalten. Dementsprechend wurde der ÜNB dazu verpflichtet, all die Einspeisungen von den Quellen der erneuerbaren Energie aufzunehmen und diese zu vermarkten. Dabei wurde der ÜNB mit den speziellen Charakteristika des neuen „Marktprodukts" konfrontiert: durch den hohen Anteil der stochastischen Windenergie an dem aufgenommenen Energiemix, wird die Verlässlichkeit eines solchen Marktgeschäfts gefährdet. Damit die Windeinspeisungen, die der ÜNB aufnimmt, den Anforderungen des deutschen Energiemarkts entsprechen können (diese müssen z.B. als unlimitiertes Gebot platziert werden[2]), muss der ÜNB über eine zuverlässige day-ahead Prognose verfügen. Deutsche ÜNBs verwenden bei ihrer Arbeit eine Metaprognose, gewichtet von den mehreren Windenergieprognosen, die in den letzten Jahren entwickelt wurden (z.B. die von energy & meteo systems GmbH, EuroWind GmbH, IWES). Die Mehrheit dieser Prognosen basiert auf numerischen Wettervorhersagemodellen, welche die ÜNBs über die in jedem Zeitpunkt zu erwartende Windenergiemenge informieren. Damit reduziert sich weitgehend die der Windenergie zugeordnete Zufälligkeit. Nichtsdestotrotz sind die verbleibenden Abweichungen zwischen der day-ahead Prognose und den tatsächlich auftretenden Windeinspeisungen der Grund für den immensen zusätzlichen Kostenaufwand (im Stellenbereich von Milliarden Euro) wie für den ÜNB (z.B. für die Leistungsvorhaltung und das Einsetzen der Regelenergie) als auch für den Letztverbraucher (erhöhte Elektrizitätstarife infolge der Umwälzung der genannten Zusatzkosten). Eine sinnvolle Maßnahme um diesen Abweichungen entgegenzuwirken wäre, die Qualität der day-ahead Prognose, die der ÜNB als Service bekommt, zu verbessern. Dementsprechend groß ist die Forschungsgemeinschaft, die sich mit dieser Fragenstellung auseinandersetzt. Der ÜNB an sich hat allerdings keine Möglichkeit die potentiellen Fehlerquellen zu beeinflussen. Die begrenzten Informationen, die er zur Verfügung hat (die gewichtete day-ahead Prognose und die Information über die tatsächlich aufgetretenen Windeinspeisungen, die er bekommt mit der Verzögerung von 24 Stunden) zwingen den ÜNB dazu, solche Methoden für die Optimierung seines Marktverhaltens aufzusuchen, die mit diesen wenigen Angaben arbeiten können. Genau diese Tatsache macht die vorliegende Arbeit neuartig, da die präsentierten Methoden – Q-Learning und Kalman-Filter – diesen Anforderungen entsprechen. Ihre Leistung wird binnen des nachsimulierten EEG-Ausgleichsmechanismus getestet und anhand von realen Windeinspeisungsdaten verifiziert. Die erreichten Ergebnisse werden mit den üblichen statistischen Kennwerten bewertet.

[2] Das bedeutet einen Stundenkontrakt zu bieten ohne dabei einen Preis zu definieren

Contents

Abbreviations

General

AC	alternating current
AGC	automatic generation control
ANN	artificial neural networks
ARCH	auto-regressive conditional heteroscedasticity
ARMA	auto-regressive moving average
BG	balancing group
DC	direct current
FACTS	Flexible AC Transmission Systems
FEC	final electricity consumption
GSO	grid system operator
HE	horizontal equalisation
IEM	Internal electricity market
IT	information technology
KF	Kalman filter
MAE	Mean Average Error
MDP	Markov decision process
MOS	model output statistics
NWP	numerical weather prediction
OTC	over-the-counter (electricity market)
PV	photovoltaics
QL	Q-Learning
RES	renewable energy sources
RES-BG	balancing group for renewable energy sources
RMSE	Root Mean Squared Error
SCADA	Supervisory Control and Data Acquisition
SDE	Standard Deviation of Errors
SV	sublimation value
TSO	transmission system operator
WPF	wind power forecast
WPMS	Wind Power Management System
WPPT	Wind Power Prediction Tool

Authorities

BDEW	Federal Association of Energy and Water (Bundeverband für Energie- und Wasserwirtschaft)
BMU	Federal Ministry for the Environment, Nature Conservation and Nuclear Safety (Bundesministerium für Umwelt, Naturschutz und Reaktorsicherheit)
BNetzA	Federal Grid Agency (Bundesnetzagentur)
EC	European Commission
FERC	The Federal Energy Regulatory Commission (USA)
NERC	The North American Electric Reliability Council

Legislative acts

Abbreviation	English	German
AusglMechV	Ordinance on the Further Development of the Nationwide Equalisation Scheme	Verordnung zur Weiterentwicklung des bundesweiten Ausgleichsmechanismus
EEG	The German Renewable Energy Sources Act	Gesetz zur Neuregelung des Rechtes der Erneuerbaren Energien im Strombereich und zur Änderung damit zusammenhängender Vorschriften
EnWG	Energy Industry Act	Gesetz über die Elektrizitäts- und Gasversorgung (Energiewirtschaftsgesetz)
GG	German Constitution	Grundgesetz
MAP	Market incentive program	Marktanreizprogram
StrEG	Federal Electricity Feed Law	Stromeinspeisungsgesetz
StromHVO	Regulation (EC) 1228/2003 on Cross-Border Exchanges in Electricity	Stromhandelsverordnung
StromNZV	Regulation on the access to electricity supply grids	Verordnung über den Zugang zu Elektrizitätsversorgungsnetzen (Stromnetzzugangsverordnung)

Glossary of terms

In this thesis some specific terms are used that need separate explanation. These are:

Horizontal equalisation	Part of the Nationwide Equalisation Scheme. The four Transmission System Operators (TSOs) carry out among one another a „horizontal equalisation of burdens“. This means that the electricity produced from RES plants is allocated to the four TSOs according to the shares which the electricity sales in the different control areas of TSOs have in total electricity sales in Germany (RES-Quota)
Sublimation values (SVs)	Energy amount that must be marketed by the TSOs, themselves or jointly, in a non-discriminatory and transparent manner, on the day-ahead spot market of an electricity exchange
“Real-time” values	Extrapolated actuals of wind power feed-in, received from online measurements of representative wind farms (online estimation). Used by the TSOs as a reference value for wind power feed-in really occurred. Becomes available with the time lag of 24 hours.

Chapter 1

Introduction

1.1 Motivation

The majority of electric utilities in Europe – and the most of the world – are structured around large, central power stations, connected to transmission systems which deliver electricity to end customers on distribution networks. The output from these power stations is controlled, so that the stations are "dispatched" (i.e. are able to produce) in the order of increasing cost (short-run marginal costs) as the demand rises. Such centralized and integrated power systems, with the power generated and delivered by monopoly operators, became the dominate pattern of electricity system development around the world.

However, in the past twenty years, this pattern has begun to break down. Altering of demand, input costs, technology developments and environmental pressure have led to changes in regulatory structures allowing new entrants and new decision-makers acting on the electricity market. The whole context for decision-making concerning power systems is changing, in ways that have profound implications for renewable energy.

Renewable energy sources (RES) are promoted as a prospective means of moderating the risks associated with high fossil fuel import dependence. The parallel development of environmental awareness and the emergence of environmental political parties in Europe provide an equally powerful rationale for government investment in RES.

The renewable sources of "primary electricity" – those such as wind, solar, hydro, wave and tidal energy that produce electricity directly from mechanical or photoelectric conversion – differ from most conventional power sources in several important ways. Their output is "fluctuating": it follows the fluctuations of the natural cycles. They are usually available on much smaller scales; as such they can be installed in relatively short time and would usually connect to distribution networks rather than feed directly into the high-voltage transmission system (except of large on-shore and especially off-shore wind parks). Finally, they are cheap to operate once constructed; the main cost lies in the construction.

Additionally renewable sources of electricity build the basis for substantial climate protection. Renewable energy and energy efficiency technologies are now of prime importance for creating a clean energy future for not only the nation, but the world. It increases diversity of energy supplies and its use can significantly reduce greenhouse gases and other pollutants.

The deployment of renewable energy requires appropriate economic, market and regulatory instruments. The so-called “20-20-20” climate change proposal of the European Commission is one of numerous measures undertaken in Europe to promote renewable energy. In its second Strategic Energy Review the European Commission strives for sustainability, competitiveness and security of energy supply, by reducing greenhouse gas emissions by 20%, increasing the share of renewables in the energy consumption to 20% and improving energy efficiency by 20%, all of it by 2020 [1].

Implementation of the EU ’s targets is primarily dependent upon on the formulation of framework conditions at national level. For Germany factors that favour the continued, concerted expansion of RES on its national level are as follows:

- Reducing the dependency on energy imports (energy supply reliability);
- Balanced mix of energy sources based on efficiency and climate-friendliness;
- Conserving limited fossil resources;
- Environmental and climate protection.

Due to sustainable pursuing of these goals the advancement of renewable energies in Germany is often cited as a model success story. The German government launched a comprehensive series of promotions for renewable energy in the early 1990s, which has since been augmented with additional legislation and policy actions to increase renewable energy use. Most of these policies are embedded in a larger set of environmental, economic, and security policy considerations.

These efforts led to the emergence of a new vital and powerful industry and adoption of legislative acts (the EnWG[3] and the EEG[4]), which support the propagation of renewable energies in Germany and their rapid technological development.

A special role within this special regulatory framework is assigned to Transmission System Operators (TSOs), which are responsible of coordination of feed-in from renewable energy sources within their control area. In contrast to the previously performed technical obligations of a TSO (ensuring of network availability, congestion prevention and management, ensuring the system stability), this new responsibility requires from TSOs to overtake the role, which is

[3] Energiewirtschaftsgesetz (Gesetz über die Elektrizitäts- und Gasversorgung, Energy Industry Act)
[4] Erneuerbare-Energien-Gesetz (Gesetz für den Vorrang erneuerbarer Energien, The German Renewable Energy Sources Act)

sometimes similar to the tasks of a *market trader.* Within this role a TSO must fulfill following duties:

- registration of different volumes and periods of generation of renewable energy in its balancing group (BG) (which is normally coincide with TSO's control area[5]);
- provisional equalisation of differences between RES feed-in and a share of a particular TSO on RES-consumption amongst the TSOs without undue delay (horizontal equalization (HE));
- marketing of all RES feed-in, available in the control area, on the energy market (on the European Energy Exchange (EEX[6]))

As already mentioned the output of RES power plants is of stochastic nature. This stochastic is mainly caused by the significant share of **wind energy**, which experiences a tremendous growth in Germany now. Whereas in the mid-1990s, the average installed capacity per wind turbine was still less than 200 kilowatts (kW), in the year 2008 the average installed capacity was already on average 1.2 MW per power plant; today a modern standard plant has 2 MW. In the meanwhile there are multi-megawatt plants with the plant capacity of up to 6 MW offered [21]. Existing wind power capacity in Germany in 2008 is totalled to 24 GW (second place in the world slightly overtaken by the United States (25 GW) after long-time wind power leadership [17], nearly 50% of all RES-feed-in in Germany).

Due to this meaningful share of wind, it is of particular difficulty to sublimate the stochastic RES-energy feed-in into a "standard market product" in order to market them as it is ordered by corresponding legislative acts. Among the most important obstacles for wind power sublimation following of its special characteristics are to be mentioned:

- **Intermittency**. When there is no wind, no power is generated; the wind comes and goes, and does not always blow with the same intensity. Because of this intermittency, the supply of wind power will fluctuate more than that of traditional generating sources;
- **Non-dispatchability**. Wind power enters an electrical grid whenever there is adequate wind, and therefore cannot be called upon to serve load;
- **Low marginal running costs** resulting in a low market clearing price. Since the introduction of negative prices on the EEX on 28.04.2008, the outcome of an market auction can have good chances to result in minus values at calculation of market clearing price (as e.g. on 22.12.2008, hour 4-5, price on the EEX -101€/MWh [31]). It would mean that the TSO as supplier must pay for the buy-out of its wind power quantities. These costs become thereafter a part of electricity bills of final customers;

[5] A control area is usually coincident with the territory of a company, a country or a geographical area, physically demarcated by the position of points for measurement of the interchanged power and energy to the remaining interconnected network, operated by a single TSO, with physical loads and controllable generation units connected within the control area [2].

[6] Since 2009 all short-term power commodities are traded on EPEX Spot SE (as a consequence of merge of EEX (Germany) and Powernext (France)). However, in this thesis the name "EEX" continues to be used for the purpose of convenience and common understanding.

- **Forecasting difficulties**. This lack of 100% predictability in power output makes wind power particularly difficult to trade in a competitive market due to the imbalance charges imposed for deviating from the contracted position or the necessity to apply the expensive regulating power. The occurring costs must then also be paid by end customers.

Since a TSO must care about a fair pricing policy for its services (which would mean it must cover its costs but in the same time can not force up the electricity prices) the wind power characteristics listed above must be considered by a TSO for integrating the wind power feed-in into electricity market and elaborating its market performance.

1.2 Objectives

This thesis is concerned with investigation of methods that can support a TSO in its everyday business – marketing of received wind power feed-in. The special attention thereby is devoted to the special characteristic of wind energy – the lack of its 100% predictability.

Wind power prediction systems which improve the technical and economical integration of wind energy into the electricity supply system and are widely used among TSOs are already available (see i.e. [36], [37], [41], [47] for detailed overview). The majority of them is based on numerical weather predictions models (NWP) and provides the information how much wind power can be expected at which point of time. Thus they announce the variations in the electricity production of wind farms in advance and largely reduce the degree of randomness attributed to wind energy. The day-ahead forecast of wind energy feed-in a TSO receives each day is the weighted combination of several of such wind power prediction systems (see [26], [46], [52], [53]).

This day-ahead forecast of the available wind energy output in TSO's control area builds the basis for conduction of market deals for energy delivery on the next day. However, the actual real-data of wind power feed-in differs significantly from the day-ahead forecast a TSO had.

This imperfection in forecasting results in deviations between the day-ahead contracted volumes and the real energy quantities occurring. The equalisation of these deviations causes significant costs, e.g. through an input of an expensive additional energy source, available for network regulation in this certain moment. These additional expenses are further pushed down to the end customers and result in increased electricity tariffs.

In order to avoid or at least to reduce this additional burden for end-users the market clearing price, a TSO receives for bidding of its wind power quantities, must therefore be accordingly high (in order to cover the additional costs). However, in accordance with the German RES regulatory framework, a TSO must accept every price that is settled for each hour contract (even the negative ones). Therefore the only possibility to avoid these high costs is to predict the "real-time[7]" data of wind power feed-in on the day-ahead as exactly as possible.

Correspondingly, ***the objectives of this thesis are to find the methods to optimize a TSO's market performance at marketing of wind power feed-in and investigate their effectiveness***. The effectiveness means in this case that these methods must improve the quality of day-ahead wind power forecast, a TSO receives, in such a way, that the deviations, occurring in the day of delivery could be hold as small as possible. The difficulty thereby is that the only information a TSO has on its disposal is the weighted day-ahead WPF it receives as a service and the "real-time" data that it is given in 24-hours-delay. This substantial boundary condition turns the investigated problem into a rather novel research topic. The methods used for optimization of TSO's market participation are determined by the author as **"post-processing" methods**, since they forecast the "real-time" data regarding the already existent day-ahead forecast. Consequently, this thesis is not about wind forecasting methods as such, but rather about how to determine the level of contract energy to be sold on a short-term energy market such as EEX.

Additionally there are some *requirements* that have to be fulfilled by these optimization methods:

- rely on limited input data; the only data source the operator can use is these two time series described before: day-ahead WPF (weighted WPF from several providers) and ex-post "real-time" values;
- not claim much time for calculations. It must be rather a simple model, which is easy to use. A possibility to change the initial conditions must be ensured;
- the calculations must consider the current RES legislation (include regulations of the HE);
- the model must outperform the initial day-ahead forecast;
- within this system it must be allowed to test different marketing strategies;
- in case of implementation by a TSO a possibility to change the initial model conditions must be provided.

1.3 Structure

After this Introduction, Chapter 2 is devoted to general description of a problem a TSO is faced with. It is started in section 2.1 with an explanation of a traditional role of the TSO in power industry. Usually a TSO is responsible for operation of national energy grid, particularly with regard of guarantee the nominal grid frequency of 50 hertz, ensuring the system stability in its control area as well as other obligations. Faced now with unbundling regulations (described in section 2.2.1) and intense growth of RES in Germany (section 2.2.2) it assumes a new

[7] Here and further real-time data is written with quotation marks ("real-time" data), because the data used is in fact the extrapolated values of recently measurements from selected representative wind farms, used by TSOs as basis for compensation in the respective EEG balancing group. The actual generated energy can deviate from this "real-time" level

responsibility of coordination of a RES balancing group (EEG-Bilanzkreis) TSO within the German national equalisation scheme for renewable energies (section 2.2.3). Within this responsibility the TSO acts like a market trader.

Section 2.3 explains accordingly the special obligation a TSO must fulfill within this new responsibility. Acting like a market trader means in particular to bid the received RES power feed-in on the energy market. Almost the half of these volumes consists of stochastic wind power. It is therefore important to analyze how the special features of this variable energy source influence a TSO's market participation. "Merit-Order"-Effect of wind power on the energy market as well as the legislative support of RES in Germany makes the relevance of accurate wind power forecast (WPF) of particular importance for the effective participation of a TSO on the power market.

Continuing the theme of significance of accurate WPF in section 2.4, section 2.4.1 gives a general overview of existing WPF tools. Different prediction horizons as well as the potential users of WPFs are presented. Two approaches to transform the given numerical weather data into the power output of a wind turbine (statistical and physical) are explained in detail. Finally the wind power prediction tools that are in use by German TSOs are introduced. Section 2.4.2 emphasizes the considerable consequences of forecast errors and their particular meaning for a TSO's as market player. It is shown that especially the deviations between the day-ahead WPF and its "real-time" data is the reason for significant cost expenditures of a TSO, e.g. for control energy.

In conclusion section 2.5 summarizes all the circumstances a TSO must work with. Legislative, market and that on the part of wind power restrictions for TSO's market participation are demonstrated. It is obviously now that a TSO has only limited abilities to optimize its market behaviour and reduce the costs connected with marketing of wind power. In fact only one possibility to influence the quality of TSO's market participation is to decrease the forecast error embedded in an initial day-ahead WPF a TSO receives every day, i.e. **the quality of existing day-ahead WPF that are currently in use by German TSOs must be improved**.

Chapter 3 is subsequently devoted to the optimization methods which application by German TSOs can influence the quality of the initial day-ahead forecast. Being a receiver of WPFs as of service a TSO has no leverages to influence on the modelling assumptions and techniques used within these forecasts. It means it has no control over errors contained in the NWPs, SCADA, prediction models and must accept them as they are. The only opportunity to discover whether its marketing decisions were right is given on the next day, when the "real-time" values (online estimation data) are available. That is why the proposed methods are defined by the author as **"post-processing" methods**, since their accuracy can be improved only after they were produced. Subsequently the obtained prediction data must be assumed as an isolated time series with implied inaccuracy nature. Two methods are presented: the Q-Learning and the Kalman filter. Motivation for this selection (section 3.1) is followed by the description of their mathematical background (section 3.2) and the particular application for the optimization task (section 3.3).

In Chapter 4 the conducted case studies are presented. Besides testing their performance influence of internal modelling parameter on the prediction results was tested. Important achievement in the case of the Q-Learning algorithm was the definition of optimal learning/prediction intervals for each of four TSOs.

All the results were evaluated with the help of commonly used error measures, whose description is to find on the beginning of the Chapter (section 4.1). It is shown that both methods bring significant improvement of prediction data in comparison with the initial day-ahead forecast.

Chapter 5 is devoted to the validation of the algorithm performance. Whereas the performance of the Kalman filter always brings clearly defined results regardless the variants of testing data, the self-learning characteristics of the Q-Learning algorithm are tested on their optimization potential using optimal learning/prediction intervals, elaborated within the corresponding case studies. In this way application peculiarities of this method are analyzed.

Finally, Chapter 6 contains an overall summary with conclusions and outlook.

Chapter 2

Role of a German TSO in the unbundled environment

The power transmission system is complex, costly and critical to the national economy. This system developed from the earliest distribution system surrounded Thomas Edison's 1882 Pearl Street Station in lower Manhattan into a sophisticated network involving interconnected power plants and power lines that operate at many different voltages (Figure 2-1).

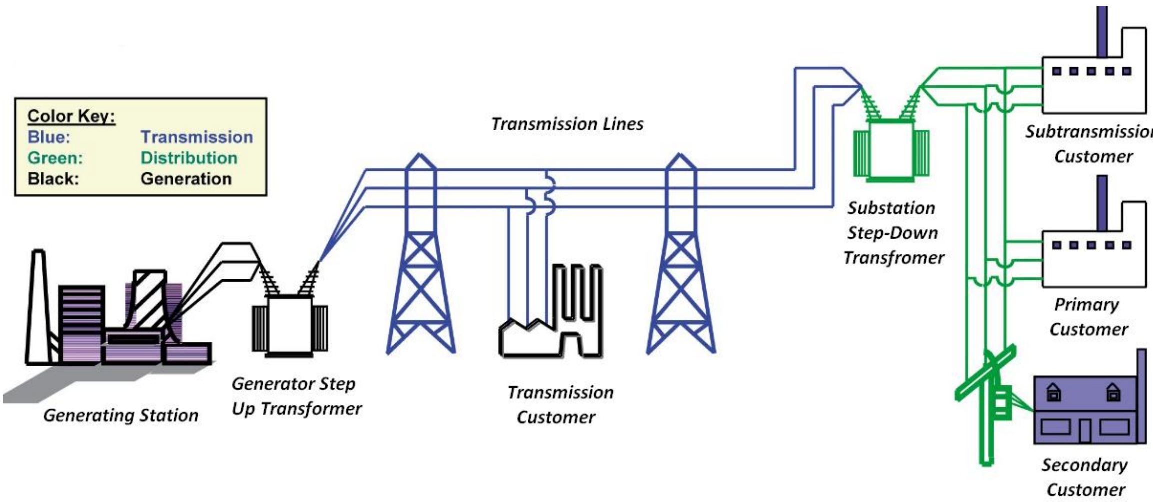

Figure 2-1: Basic structure of the electric system

The fast transformation of the power industry from a local to an interstate one occurred for four main reasons: reliability, flexibility, economics, and competition. Broadly, a strong transmission system 1) improves the reliability of the electric power system, 2) gives electricity customers flexibility to diversify the mix of fuels that produces their electricity by giving them access to power plants, 3) improves the cost structure of the entire industry by giving low-cost power plants access to high-cost power markets, and 4) enables competition among power plants by giving more plants access to more markets [3].

Transmission system operator (TSO) facilitates the power system by making it available for interested parties by planning, constructing and operating it in accordance with both political and physical laws. It is also responsible for keeping the power system in balance, and thus it is responsible for the overall physical management and control of the power system. Technically this means that the frequency is maintained at nominal frequency.

At the same time a TSO is responsible for ensuring that the power transmission system is constructed in accordance with the market's needs and that socioeconomic criteria are used for the solutions that are selected. The TSOs may weigh different solutions such as agreements to disconnect consumption and the construction of new power lines up against each other and choose the most profitable on the basis of an overall socioeconomic assessment.

TSOs are the organizational backbone of the electrical power grid, and link power generators with distribution companies according to transparent rules. They are financed by charging a network fee proportional to the annual peak load they carry. Consequently, in their essential nature TSOs are not-profit organizations; their action is based on non discrimination of market players and continuous good performance of their power system. They are neutral bodies, whose independence is established by the Internal electricity market (IEM) Directive[8] of the European Parliament and the Council [4]. TSOs are the ones that ensure that any changes in the regulations can be effectively implemented on a day-to-day practical basis, without jeopardising the secure operation of the interconnected power systems.

In order to understand the nature of TSO’s operation fields Section 2.1 presents a short overview of its main tasks.

2.1 Basic responsibilities of a TSO

According to Article 9 of the IEM Directive each transmission system operator shall be responsible for [4]:

- “ensuring the long-term ability of the system to meet reasonable demands for the transmission of electricity;
- contributing to security of supply through adequate transmission capacity and system reliability;
- managing energy flows on the system, taking into account exchanges with other interconnected systems. To that end, the transmission system operator shall be

[8] Internal Market in Electricity Directive is the Directive 2003/54/EC of the European Parliament and the Council of 26 June 2003 concerning common rules for the internal market in electricity and repealing Directive 96/92/EC is based in the Treaty establishing the European Community, and in particular Article 47(2), Article 55 and Article 95 thereof. Note: The Directive 2003/54/EC has been replaced by the Directive 2009/72/EC.

responsible for ensuring a secure, reliable and efficient electricity system and, in that context, for ensuring the availability of all necessary ancillary services insofar as this availability is independent from any other transmission system with which its system is interconnected;

- providing to the operator of any other system with which its system is interconnected sufficient information to ensure the secure and efficient operation, coordinated development and interoperability of the interconnected system;
- ensuring non-discrimination as between system users or classes of system users, particularly in favour of its related undertakings;
- providing system users with the information they need for efficient access to the system".

National German regulatory framework for TSO operation supports the European regulations by means of the EnWG, [5] and the Transmission Code 2007 [6]. In particular in accordance with §12 of EnWG TSO are obligated to ensure the sustainable functioning of the high voltage grid, satisfaction of demand on transmission of electricity and, substantially contribute to security of supply through adequate transmission capacity and reliability of the network. §7 of Section 1.1 in the Transmission Code 2007 claims in its turn for the orientation of the technical requirements of TSO operation on a trouble-free operation of the transmission network and control of disturbances. On this basis, the cross-border exchange of power between the synchronously-operated transmission networks, and non-discriminatory data provision must be handled.

In general, standard traditional responsibilities of a TSO can be gathered into the following several fields:

Ensuring of network availability

Network availability can be defined as the provision of ability of the electric system to supply the electrical demand and energy requirements of customers at all times, taking into account scheduled and unscheduled outages of power lines and power plants. The transmission system gives power users the ability to draw from a diverse set of power plants in different locations and with different operating characteristics. If the transmission system is robust, with a certain amount of redundancy built in, it can withstand the failure of its most critical lines or other components. This is referred to as single contingency analysis, or N-1 criterion [3].

In order to ensure this network provision in accordance with the regulatory requirements the transmission system must be regularly maintained. Typical range of maintenance tasks usually involves regular network checking, troubleshooting and resolving of problems on the network, troubleshooting of related hardware attached to the network, setup and changes to security police.

Congestion prevention and management

The adequate transmission capacity is ensured if the scheduled power flows are executed as it was planned. If it is not the case and the safety or reliability of the electricity system in the control area is threatened or disrupted, that means that a certain kind of congestion exists.

Congestion is according to Art. 2 Abs. 2 lit. c of Regulation (EC) 1228/2003 on Cross-Border Exchanges in Electricity (StromHVO, [7]) "a situation in which an interconnection linking national transmission networks, cannot accommodate all physical flows resulting from international trade requested by market participants, because of a lack of capacity of the interconnectors and/or the national transmission systems concerned". Such situations mean a danger to safe and reliable power supply, and in that cases TSOs are entitled and obliged to eliminate the hazard or failure in accordance with §13 EnWG and §15 of the Regulation on the access to electricity supply grids (StromNZV, [8]) by means of

- network related measures, in particular through network circuit reconfiguration, and
- market related measures, such as the use of balancing energy, contractual agreed switchable loads, information about bottlenecks and congestion management and mobilization of additional reserves.

Both of these kinds of measures, which a TSO can engage for eliminating of congestion threat, are explained in Annex of Transmission Code 2007. They are presented in Table 2-1 and Table 2-2 for the sake of completeness.

Table 2-1: Network related measures to be applied in accordance with §13 Abs.1 EnWG [6]

Measures	Explanation
Topology measures	Consist of providing (if necessary, in coordination with neighboring operators) of switching operations in the own network area of a TSO, including the interconnecting lines, in order to influence the load flow in the network
Exploitation of operationally allowable tolerance bands (current and voltage)	Short-term overloading of operational equipment (within the technical possibilities, without violating of the technical rules)

Regulation (EC) 1228/2003 also contains rules to ensure the security of the networks in the context of congestion management. According to them TSOs must put in place coordination and information exchange mechanisms. The information published shall include a general scheme for the calculation of the total transfer capacity and the transmission reliability margin based upon the electrical and physical features of the network (Art. 5 Abs.2 StromHVO).

If the emergence of congestion cannot be prevented with the help of above mentioned measures, TSOs are required to manage the available power network capacity according to market-oriented, transparent and non-discriminatory procedures (§15 Abs.2 StromNZV, Art.6 Abs.2 StromHVO). Limited feed-in and transmission capacity can be allocated through different congestion management methods, such as explicit/implicit auctions, market coupling (including open market coupling) and hybrid or special forms of them.

Table 2-2: Market related measures to be applied in accordance with §13 Abs.1 EnWG [6]

Measures	Explanation
Utilization of balancing energy	Application of contractual agreed balancing energy. The scheduling is carried out accordingly to the requirements of network control
Contractual agreed switchable loads	Due to connection and disconnection of loads, the power balance in the control area can be controlled. For this purpose the corresponding contracts about the switchable loads must be agreed. The scheduling is carried out in accordance with to the respective requirements and contractual agreements
Preventive congestion management	Taking such measures as pro-rata reductions and auctions as well as non-acceptance of intra-day schedules in due time
Mobilization of additional reserves by the TSO	If the applied balancing energy is not sufficient to compensate the power balance in a control area, additional reserves must be mobilized. This can be previously unused power from power plants; starting-up of unutilized units, as well as temporary help by neighbouring TSOs (delivery of free tertiary control reserves)
Countertrading	Preventive or curative counter deal (induced by TSO)
Redispatch	Preventive or curative influence on power generation by TSO

In any of these cases, the use of congested interconnections and/or the transmission networks to their maximum capacity, complying with safety standards of secure network operation must be ensured. Therefore TSOs shall, as far as technically possible, net the capacity requirements of any power flows in opposite direction over the congested interconnection line. Having full regard to network security, transactions that relieve the congestion shall never be denied (Art.6 Abs.5 StromHVO).

System stability

It is commonly known, that electricity cannot be stored efficiently. Apart from indirectly storing it in fuel stockpiles or in water held above hydroelectric dams[9], there is no way of creating a substantial stockpile of electricity. Therefore production has to cover demand on an instantaneous basis. That is what is called guarantee the system stability. Accordingly, power supply is guaranteed in such a way that the electricity demanded in the withdrawal points must be always added in the same amount in the different delivery, in order to ensure the current supply of all participants.

According to [9] power system stability may be broadly defined as the property of a power system that enables it to remain in a state of operating equilibrium under normal operating conditions and to regain an acceptable state of equilibrium after being subjected to a disturbance.

[9] Besides of potential energy that can be stored by pumping water up hill, kinetic energy can also be stored in rotating generators, but all of these stores of energy must be converted to electrical energy by the process of generation before they can be delivered

Continuous development of power system technologies, national and international energy policy makes complex reliable operation the power grid more demanding and, consequently, forces TSOs to undertake new obligations. So, for example, the unbundling provisions of the EnWG caused by an international trend to liberalization in energy policy resulted in Germany in a number of concrete commitments to separation of the network activities of TSOs (a so-called "natural monopoly") from the market areas. The aim of the legislation is the supply of transparency and creation of non-discriminatory design for management of network operations. In addition governmental support of renewable energies, in particular of wind energy led to change of traditional tasks of the German TSOs, followed by acquiring of the new roles by them. Respective influences of current regulatory framework on the TSO’s tasks are discussed in the next sections.

2.2 New regulations and TSO’s changing role

For almost ten decades power industry all over the world was organized as a vertical integrated monopoly organized, often in state control. Since the beginning of the 90s of the 20th century, however, there is a worldwide trend, starting from the highly industrialized countries, to break the vertical integration and privatize state property in order to make the essential parts of the industry more competitive. This trend led to the current situation in the German power industry, where TSO are acting as independent authorities. Their responsibilities e.g. for ensuring of non-discriminatory grid access for third party, transparent grid management, were partly described in previous sections. The goal of this part is to give an overview of the background reasons for an actual development of power policy and its consequences for TSOs regarding the involvement of them into the new terrain – that of power market.

2.2.1 Unbundling

As it is outlined in [10], liberalization of the energy sector in Europe and the formation of internal European markets in electricity and gas have been conceived with the idea of benefiting European industry and consumers. Achievement of the benefit necessitates creating efficient and competitive markets and offering higher quality and more varied services to energy users at lower prices. However, for liquid markets to evolve and function effectively, it is crucial that new market entry is made possible and that there are a sufficient number of participants able to compete with each other. This can only be achieved through providing retail and wholesale market entrants with solid guarantees that they will have unimpeded access to the grid and to customers on a non-discriminatory basis. The independence of transmission system operators ranks high among the guarantees required from a new market participant’s perspective.

To ensure independence of a network operator it is important to prevent situations where it may face a conflict of interests and incentives. Separation of activities proves to be the most efficient way of solving the problem of entanglement of production and supply (as activities susceptible to competition) on the one hand, with transmission and distribution functions (which tend to be natural monopolies) on the other, within vertically integrated energy entities (Figure 2-2). **Unbundling** is the term normally used to refer to such structural solution [10].

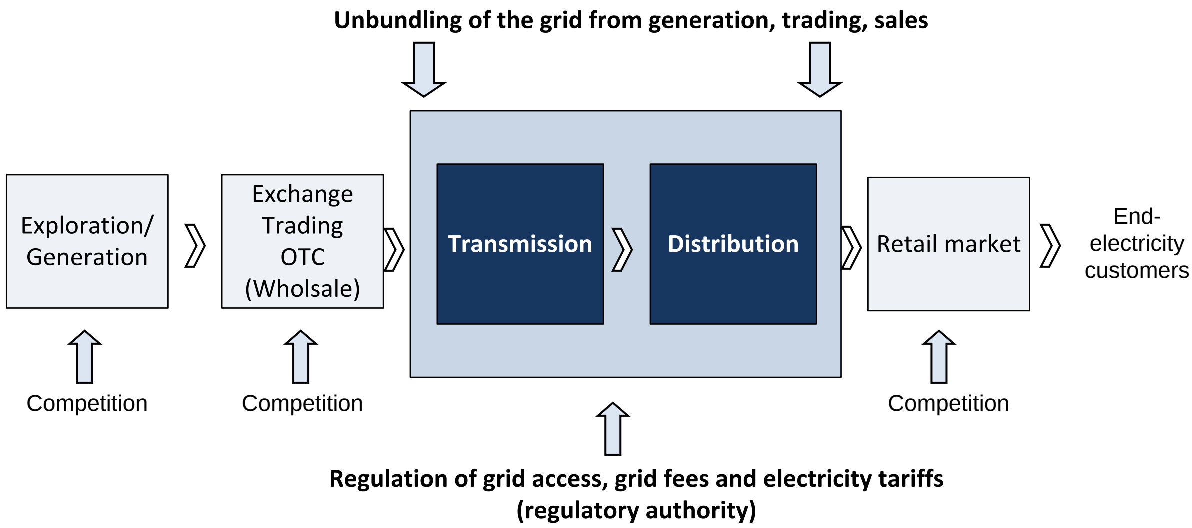

Figure 2-2: Unbundling scheme

Unbundling of activities within a former vertically integrated company minimises distortions in a single European electricity market, by ensuring transparent and non-discriminatory terms of transmission access for third parties and curtailing the risks of cross-subsidisation of the generation and supply activities of incumbents. In Germany unbundling is regulated by Part 2 §§6-10 of the EnWG.

Unbundling can be implemented in form of legal unbundling, functional unbundling, unbundling of accounts and ownership unbundling. The ownership unbundling is the most severe form of unbundling and supposes the strongest interference in the business freedom in the context of Article 2, 12 and 14 of the German Consitution[10] [11]. The other forms of unbundling are less intensive in their intervention. In §§ 6 et seq. EnWG these forms are applied in combination.

Legal unbundling (§7 EnWG)

The special ownership unbundling (legal unbundling) is a fairly extensive intervention in the entrepreneurial freedom of action, as the complete *separation of the grid operation* from the other energy activities is required from the parent company[11] (§ 7 Abs. 1 EnWG). It is intended through the separation of activities into different entities to increase the transparency of the mutual relationships between the various divisions of an integrated supply company. Another goal is to contribute to a diversification of business interests [11].

Legal unbundling does not imply a change of ownership of assets and nothing prevents similar or identical employment conditions applying throughout the whole of the vertically integrated undertakings. However, a non-discriminatory decision-making process should be ensured through organisational measures regarding the independence of the decision-makers responsible (Art.8 IEM Directive).

[10] (Germ.) Grundgesetz, GG
[11] (germ.) Mutterkonzern

Functional unbundling (§8 EnWG)

Operational or functional unbundling means, according to § 8 Abs. 1 EnWG, ensuring of the independence of the network operator from the parent company in the integrated utility in terms of organization, decision making and the operation of the network. § 8 Abs. 1 EnWG thus represents material requirements for the organization of cooperation within the integrated supply company additionally to the formal requirement of legal unbundling [11].

§ 8 Abs 2 EnWG contains the *prohibition of double responsibility* for individuals with final decision-making authorities in fields of grid operation and competition areas (e.g. generation, trading). The aim of the scheme is to avoid conflicts of interest. In the same time § 8 Abs. 2 No. 1 EnWG clarifies that the individuals without the aforementioned management positions have the right to work in these two separate fields. Thereby the individuals are obliged to perform their professional activity solely within one of the fields, while organizationally or disciplinary they can belong to the other). Consequently, § 8 Abs. 2 EnWG allows the organization of an integrated supply company with the so-called "shared services", e.g. with joint legal department, human resources department or IT service. In the structuring, however, there are rules concerning the informational unbundling (see below) that must be considered [11].

The purpose of § 8 Abs. 4 EnWG is to ensure the decision independence of the network operator from the parent company in the integrated supply company. In order to implement this regulation a detailed competency rule is established. In accordance to this rule the parent company receives only an overall responsibility. This includes the competence of abstract general rules such as financial plans, indebtedness ceilings or other target settings. In other respects the network operators are free in the performance of daily business [11].

§ 8 Abs. 5 EnWG regulates the duty of the integrated company to initiate a so-called compliance program[12] for non-discriminatory exertion of network activities. An employee or a department responsible for this compliance program is obliged to inform the regulative authorities about the implemented measures annually [11].

Informational unbundling (§9 EnWG)

Informational unbundling means that all operationally relevant information from the vertically integrated companies and their unbundled network operators must be kept apart. The goal is to prevent informational advantages of the integrated firms against non-integrated competitors in the upstream or downstream markets. Commercially valuable information can thereby be withheld. Such information include e.g. load profiles of network users, network customers data, such as address, meter readings, etc., supplier information and project information about new power plant capacities. To prevent the exchange of information the organizational measures, such as the establishment of so-called "Chinese Walls[13]" are needed [11].

[12] (Germ.) Gleichbehandlungsprogram
[13] A term used to describe procedures that separate the firm's departments to restrict access to non-public, material information, in order to avoid the illegal use of inside information.

§ 9 Abs. 1 EnWG obliges to confidentiality regarding all information that was obtained at the implementing of network activity.

In the case that information about the own work as the network operator should be disclosed, it must be conducted in a non-discriminatory manner (§ 9 Abs. 2 EnWG). Disclosure means a non-discriminatory treatment of network users in respect of information, information availability and information rapidness. This should be implemented e.g. in the form of a business report, but not for disclosure to any arbitrary organization [11].

Unbundling of accounts (§10 EnWG)

Unbundling of accounts means, according to § 10 Abs. 3 EnWG that the various divisions of an integrated utility company keep separate accounts. The purpose is to achieve more transparency of cost allocation. This in turn will lead to the possibility to compare the tariffs with the costs that were occurred. Moreover, the independent parts of the parent company regardless of their legal status must prepare annual reports that will be then reviewed by appropriate authorities [11].

Ownership unbundling

Ownership unbundling means the complete separation of network segments from the production and distribution segments in the integrated power supply company. The goal is to have one or more independent companies that can own the networks and operate them. For this purpose the energy corporate groups must be forced to sale their networks [11].

So far such ownership unbundling has been neither dictated by any European law nor considered in the EnWG, however, this topic dominates like no other in the current discussions regarding power economy and policy. Especially because of the significant constitutional concerns various alternative proposals to the classic expropriation are now discussed, in particular the solution through a creation of a so-called "Independent System Operator (ISO)” or a so-called "stock split[14]” [12].

For the TSO’s operation unbundling means first of all that a TSO acts as an **independent authority,** executing its responsibilities on operating, ensuring the maintenance of and, if necessary, developing the transmission system in a given area. It is not allowed to own and operate any generation utilities as well as it must not be part of any energy trading company. It must **ensure a non-discriminatory access** of all interested participants of power industry to the network area and make sure that the long term ability of the system to meet reasonable demands for the transmission of electricity is warranted. Besides of these obligations all the costs induced by the TSO’s performance and turned into **electricity tariffs are subject to be controlled** by a regulatory authority. In Germany this authority is called Federal Grid Agency[15].

Further the German TSO has commitments, considering the current development of renewable energies in Germany. Motivation of the government support of RES in Germany as well as the corresponding consequences for the German TSO is discussed in the following section.

[14] (Germ.) Aktiensplit
[15] (Germ.) Bundesnetzagentur, BNetzA

2.2.2 Development of renewable energies in Germany

The renewable sources of “primary electricity” – those such as wind, solar, hydro, wave and tidal energy that produce electricity directly from mechanical or photoelectric conversion – differ from most conventional power sources in several important ways. Their output is “fluctuating”: it follows the fluctuations of the natural cycles. They are usually available on much smaller scales; as such they can be installed in relatively short time and would be usually connected to distribution networks rather than feed directly into the high-voltage transmission system (except of large on-shore and especially off-shore wind parks). Finally, they are cheap to operate once constructed; the main cost lies in the construction (fixed cost character).

Additionally renewable sources of electricity build the basis for substantial climate protection. Renewable energy and energy efficiency technologies are now of prime importance for creating a clean energy future for not only the nation, but the world. It increases diversity of energy supplies and its use can significantly reduce greenhouse gases and other pollutants.

The deployment of renewable energy requires appropriate economic, market and regulatory instruments. The so-called “20-20-20” climate change proposal of the European Commission (EC) is one of numerous measures undertaken in Europe to promote renewable energy. In its second Strategic Energy Review [1] the EC strives for sustainability, competitiveness and security of energy supply, by reducing greenhouse gas emissions by 20%, increasing the share of renewables in the energy consumption to 20% and improving energy efficiency by 20%, all of it by 2020.

National economics following the European instructions go even further in their ambition to reduce the dependence on imported primary energy carriers. In particular, in Germany, motivated by goals of climate and environment protection, the German government’s Integrated Energy and Climate Programme was adopted [13], that aims to increase the share of RES in electricity sector to 25-30% by 2020.

Implementation of these targets is primarily dependent upon the formulation of framework conditions at national level. In Germany the factors favouring the continued, concerted expansion of RES are as follows:

- Reducing the dependency on energy imports (energy supply reliability);
- Balanced mix of energy sources based on efficiency and climate-friendliness;
- Conserving limited fossil resources;
- Environmental and climate protection;
- Creation of new jobs.

The German government launched a comprehensive series of promotions for renewable energy in the early 1990s, which has since been augmented with additional legislation and policy actions to increase renewable energy use [15]. Most of these policies were embedded in a larger set of environmental, economic, and security policy considerations.

Two issues in particular highlight the importance of environmental politics in Germany and their close relationship with developments in energy policy.

The first issue is the phase-out of nuclear power. An early energy policy action of the Red-Green government[16] was an initiative for the complete phase out of nuclear power in Germany by 2020. After years of negotiation in Parliament, legislation mandating the phase-out was adopted in April 2002. Germany now faces the challenge of replacing one-third of its electricity supply from other sources. Even though Germany's aging nuclear plants have been granted successive license extensions, these facilities are all slated for decommissioning by 2020. A combination of options including the construction of new renewable energy plants, combined cycle gas turbines, conservation, and power imports are likely to be used to offset nuclear power [15].

The second issue is greenhouse gas control. The future challenges incumbent in nuclear phase-out are compounded by the ambitious greenhouse gas emissions reductions targets adopted by the German government. Germany has agreed to a 21% reduction from 1990 levels by 2012 as part of the European Union's Kyoto Protocol commitment. Under a new EU-sponsored proposal for greenhouse gas emissions reduction in the post-2012 period, Germany may be asked to adopt a 40% reduction target (from 1990 levels) by 2020 [15].

This sustainable energy policy leveraged Germany to attain a leading position in many aspects of renewable energy use. For example:

- World leadership in installed PV capacity – approximately 3811 MWp in 2007 [14] (46% of the global market [16]);
- Among world leaders of installed wind capacity second – 23900 MW as of the end of 2008, or approximately 20% global capacity [17];
- European leadership in biodiesel consumption – 3.3 Mio tones in 2007;
- A substantial green electricity share – green electricity, including hydropower, represents approximately 14,8% of electricity generating capacity.

The most important influence on this successful development was exerted by Renewable Energy Sources Act[17] (in following EEG), which was adopted to improve, fundamentally revise and expand the previous Federal Electricity Feed Law[18], adopted in 1991. In EEG2000[19] the fixed rate basis for purchase of renewably-generated power from wind, solar, hydro, biomass and landfill gas sources, by public utilities was linked to the market price. This led to partially strong fluctuations, which reduced the investment security. Secondly, the implementation of fix remuneration rates was thought to be more differentiated. This differentiation had not to be oriented on the avoided fuel costs, but on the actual state of development of RES power plants. Furthermore, in order to provide an equitable distribution of renewable energy feed-in among all TSOs, a **new nationwide balancing mechanism** was introduced. In accordance with this scheme grid operators were obligated to purchase power from local producers. Additionally, with the liberalization of the

[16] A red-green coalition of the Social Democratic Party and The Greens led by Chancellor Gerhard Schröder governed the country from 1998 to 2005.
[17] (Germ.) Erneuerbare-Energien-Gesetz, EEG
[18] (Germ.) Stromeinspeisungsgesetz, StrEG
[19] The first EEG was passed on 1 April 2000; afterwards several new (revised) versions of EEG followed. In order to distinguish between individual law adaptations, the year, in which they were passed, are respectively indicated.

power market new roles for power market participants were defined, concerning the responsibility for receipt of RES feed-in, as well as for the remuneration payment [18].

After the passed EEG2000 an unprecedented boom started in various sectors of renewable energy industry. A particularly strong growth of 40-60% annually in the installed capacity has been made in PV, since its remuneration conditions had drastically improved. Also in the field of bioenergy the strong growth was continued, especially at biogas plants, which were additionally promoted by the market incentive program[20]. Although these two markets had the largest dynamic of growing, their contribution to the electricity generation was still of only small percentages: the PV amounted nearly 0,6% of the total renewable electricity in 2003, electricity generated from biomass (without waste) had the share of 14,3% [13], [18]. The quantitatively most important growth experienced the wind industry, which grew till 2004 in average by more than 2000 MW of installed capacity annually (Figure 2-3). The resulting amount of generated electricity in 2004 exceeded for the first time the share of hydropower.

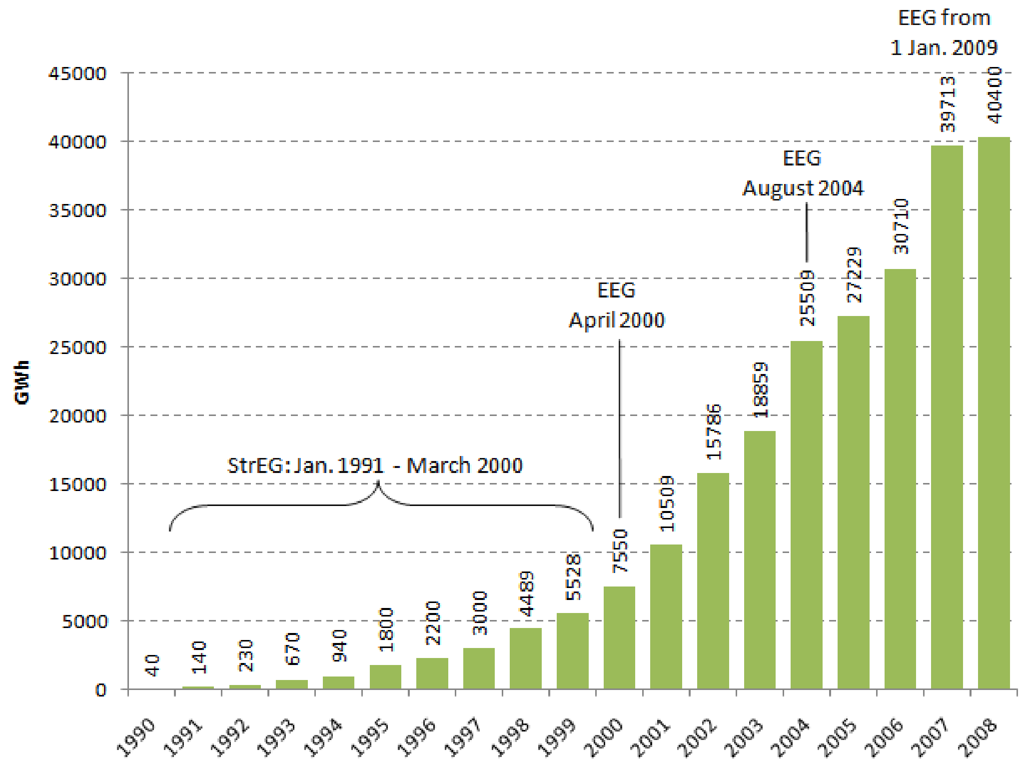

Figure 2-3: Development of electricity generation from wind in Germany 1990-2008 [21]

The new version of EEG was passed on 1 August 2004. The number of paragraphs increased from 13 to 21. New regulation for special treatment of electricity-intensive industry and greater differentiation of reimbursement rates in accordance with performance range were the innovations of the EEG2004.

The great dynamic in the development of electricity generation from RES required an intensive monitoring of the according promotion. For this reason the Federal Ministry for the Environment,

[20] (Germ.) Marktanreizprogram, MAP

Nature Conservation and Nuclear Safety[21] (in following BMU) arranged a series of research projects in order to prepare a report on the performance of the EEG2004. These reports built the main basis for the RES Experience Report[22] of the BMU [19], which was adopted by the Federal Cabinet and published in November 2007. On that basis, the renewed EEG2009 was adopted by the German Bundestag in June 2008 and became effective on 1 January 2009.

By the EEG2009 [20] the option of direct marketing of generated electricity by RES power plants' operators was introduced. Provided that the operator ensures the legally required notification of network operator, it can temporarily abandon - for at least a month - the EEG-compensation system (the reimbursement rate is not paid for this period), and sell the generated electricity (on its full amount or at shares) on the free market. It remains, however, in the regime of the EEG and may return to the system of EEG remuneration at any time, while respecting the pre-specified periods of the direct marketing [21].

A key innovation of the EEG2009 was the possibility to issue statutory instruments (§ 64 EEG2009), which allows the government to provide a whole series of adjustments and provisions additionally to the existing regulations. In consequence of this allowance a new regulatory policy was introduced by the Federal Cabinet on 27 May 2009 in form of adoption of the Regulation of the further development of the nationwide compensation mechanism[23] (in following AusglMechV) [28]. Motivated through the transparency enhancement, simplification and further development of the nationwide equalisation scheme it changes certain TSO's obligations within the previous framework. In order to understand the previous and novel responsibilities of TSO within the RES system the next subchapter is introduced.

2.2.3 German RES-balancing scheme and responsibilities of a TSO within this scheme

In view of rapid development of RES there are clearly defined rules, described in the EEG2009, which all participants that are involved in RES process are obliged to fulfill. The EEG 2009 regulates:

- "**priority connections** to the grid systems for general electricity supply of plants generating electricity from RES and from mine gas within the territory of the Federal Republic of Germany
- **the priority purchase** and **transmission** of, and **payment** for, such electricity by the grid system operators and
- **the nationwide equalisation scheme** for the quantity of electricity purchased and paid for"

As already mentioned the key innovation of the EEG2009 was the right of legislative and regulatory authorities to provide a whole series of adjustments and additional provisions to the existing RES-system. Such innovation concerning the nationwide equalisation scheme became

[21] (Germ.) Bundesministerium für Umwelt, Naturschutz und Reaktorsicherheit, BMU
[22] (Germ.) EEG-Erfahrungsbericht
[23] (Germ.) Verordnung zur Weiterentwicklung des bundesweiten Ausgleichsmechanismus (AusglMechV)

effective on 01.01.2010. In order to understand the basis of the RES-system as well as the reasons of the introduced changes both schemes are presented below.

Nationwide equalisation scheme (valid till 01.01.2010)

In order to ensure the feasibility of adopted regulations as well as to consider the rights and obligations of involved participants there is a certain mechanism emerged, called the German nationwide EEG equalisation scheme (Figure 2-4[24]).

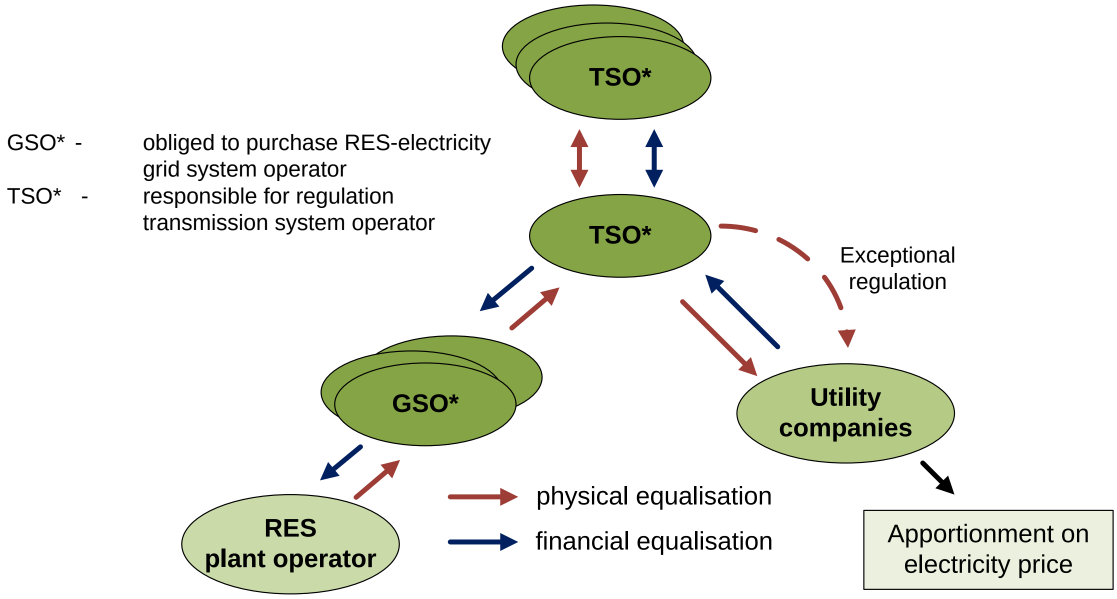

Figure 2-4: The German nationwide equalisation scheme

The EEG and other legislative acts prescribe this process as follows. According to Art. 8 of the EEG the grid system operators (GSO) are obliged to prior purchasing, transferring and distribution of the whole electricity from RES power plants. These RES-electricity feed-in, purchased by the appropriate GSO, must be then instantly transmitted to the preceding TSO. There are four TSOs in Germany: transpower stromübertragungs GmbH (**tps**[25]), 50Hertz Transmission GmbH (**50Hertz**), Amprion GmbH (**Amprion**) and EnBW Transportnetze AG (**EnBW**).

Basis for the determination of the transmitted RES electricity quantities is the data acquisition by the GSO. In each network each feed-in is measured separately. The GSO provides to the TSOs classified by feed-in-tariff types and classes monthly forecasts of:

- purchased quantities of electricity that ought to be transmitted to the preceding TSO;
- the associated total compensation (payment),
- final energy consumption (FEC[26]) [22].

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[24] Own outline, based on [22]

[25] After the acquisition of transpower by the Dutch grid operator TenneT, is TenneT the new name of transpower. However, in this thesis the former name "tps" continues to be used for the purpose of convenience and common understanding.

[26] (Germ.) Letztverbraucherabsatz, LVA

The four German TSOs receive this data, consolidate it for the respective control area and then report this information to Federal Association of Energy and Water[27] (in following BDEW).

TSOs are responsible for regulation and coordination of RES-feed-in on their control area. In accordance with Art. 36(1) of the EEG2004, they must register, “the different volumes of and periods of generation of energy…, and “provisionally equalize such differences amongst themselves without undue delay”. This process is called *horizontal equalisation* (HE) between TSOs. The volumes of energy that are equalized between TSOs correspond to the relation of the FEC in the control area of the individual TSO to the total amount of FEC in Germany, which is agreed to begin of the equalisation process in accordance with the data received from the GSOs. Consequently every TSO must only consider the amount of electricity generated from RES in its balancing group, which corresponds to its share in the whole final energy consumption in Germany. Thus the expenses of system integration of renewables are “equally” distributed among all TSOs (Figure 2-5).

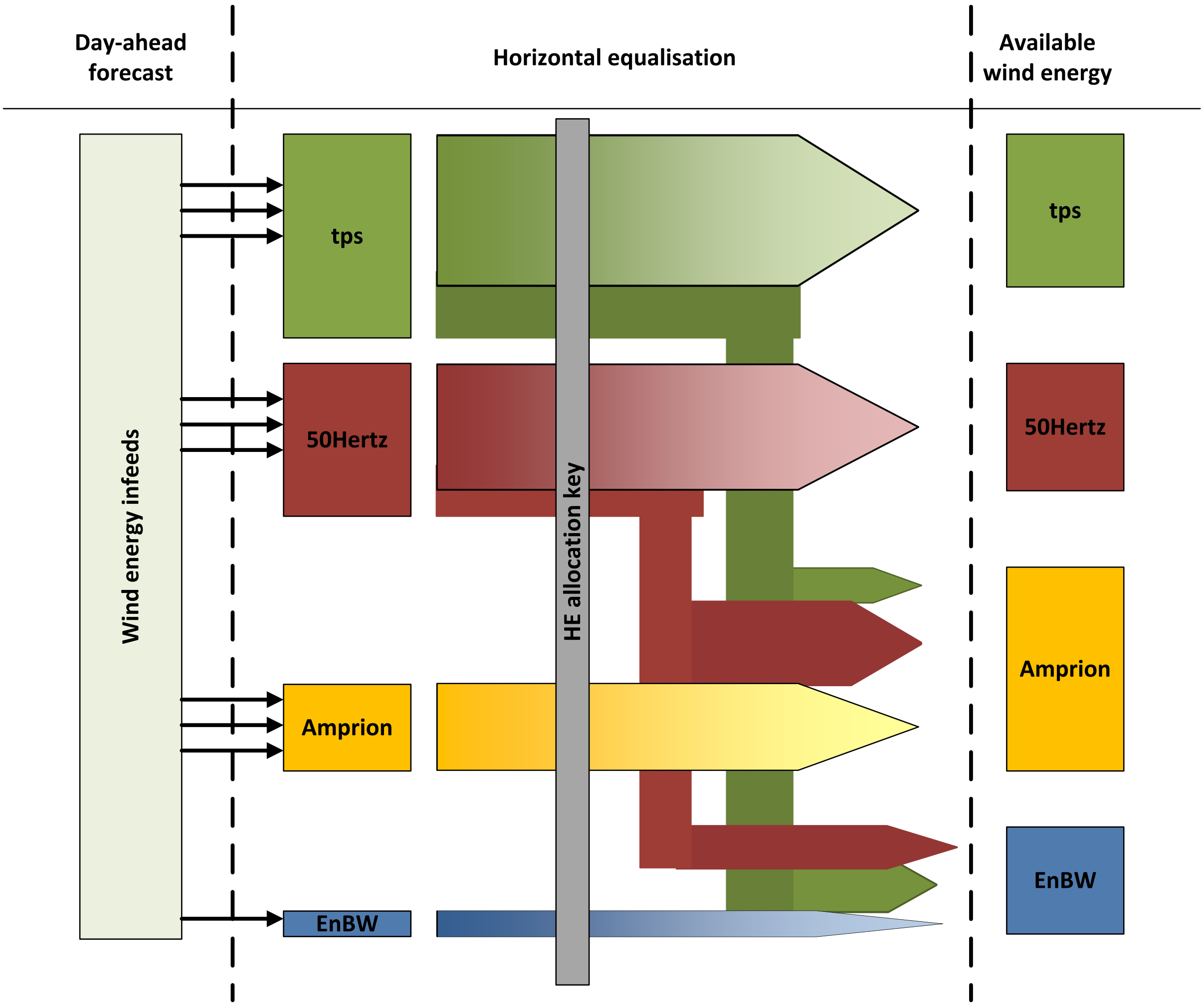

Figure 2-5: Horizontal equalisation scheme

By calculation of energy amounts, which should be horizontally equalized, the *exceptional regulation* of manufacturing enterprises or rail operators with high consumption of electricity is

[27] (Germ.) Bundesverband für Energie- und Wasserwirtschaft, BDEW

undertaken. In order to reduce the costs arising for such enterprises from delivering the electricity quantities, individual rates of purchasing the electricity generated from renewables were elaborated for them. These are referred to special final consumption[28]. The amounts of RES-energy that are not consumed by such enterprises are turned over to all other final customers[29].

This “turn over” is considered by calculation of horizontal equalized amounts through a factor called “deemed” special final consumption[30]:

$$\text{"deemed" special final consumption [GWh]} = \frac{\text{individual rate of RES [GWh]}}{\substack{\text{RES−electricity,} \\ \text{consumed by other categories of final customers [\%]}}} \tag{2.1}$$

The HE procedure initially provides the mutual exchange of the wind power forecast on the day prior to actual feed-in. It ensures the better scheduling of reserve power. The actual exchange of power quantities is then based on 1/4h-values consisting of projections from an online extrapolation model that are regularly transferred between the respective control systems of TSOs [23]. Within the HE process there is a difference between RES-quantities of wind power plants and other RES-facilities. Since the non-wind quantities are not subject to the stochastic fluctuations in power output, their feed-in can be planned in the long-term. Accordingly, the corresponding forecasted quantities are delivered from one control area into another in from of a month block. The quantities derived from wind power plants, however, are balanced between the four control areas simultaneously, based on the projections from an online extrapolation [24].

Thus within the HE a permanent exchange of power output from each TSO (source) to each other TSO (sink) is performed. The amount of electricity exchanged between the source and sink zone corresponds to the multiplication of the current RES feed-in at the "source" control area with the share of the total FEC in the "sink" control area. Since all RES feed-in are “equally” distributed between all TSOs, the overall sum of HE power flows Germany-wide amounts to 0 GWh.

At the end of the year an annual account is drawn up. Within this statement the actual FEC for all control areas is determined. Accordingly the actual RES-quantities, which are meant for the respective control area, are ascertained. The differences between the annual account and the commitments in the course of the year are balanced between TSOs till September next year.

After being equalized among individual control areas electricity must then be transferred to utility companies, which deliver it to final customers. This process is called *vertical equalisation* [31]. The utility companies have to purchase and pay for that share of electricity, which corresponds to an approximated profile of actually quantity of electricity, purchased by final consumers of utility companies. The interim profile (RES-Quota and consequently a delivery commitment of a TSO) is evaluated from monthly forecasted data of feed-in from RES and the electricity purchased by final customers by the BDEW. Conformably, the evaluation is performed monthly.

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[28] (Germ.) privilegierter Letztverbrauch

[29] These include private households, public facilities, agriculture, commerce and trade enterprises as well as all others industrial end-users that are not covered by §12 EEG 2009

[30] (Germ.) fiktiver privilegierter Letztverbrauch

[31] This part of equalization scheme is abolished in the new EEG2009. However, this process is described here since the optimization calculations in this thesis are based on the previous EEG release.

The differences between the forecasted and actual RES-feeds of the last month are determined by the BDEW. These build the basis for the correction process. The correction amounts are divided between the remaining months of the year in equal parts. They are considered at the determination of the RES-Quota.

Figure **2-6** illustrates this principle of calculation of RES-Quota by BDEW [25].

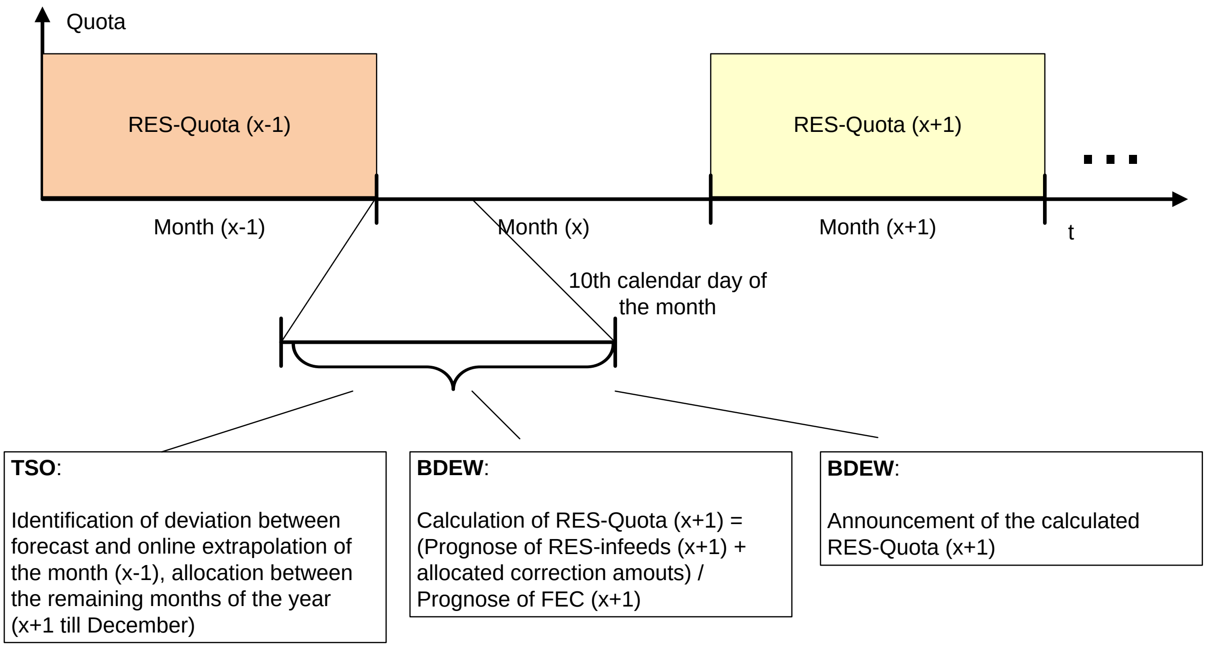

Figure 2-6: Calculation of RES-Quota by BDEW

The RES-Quota, calculated in this way, determines the TSO's delivery commitment towards utility companies. The differences occurring between the RES-Quota and the received RES feed-in must be purchased or sold on the power market. This process is called RES-sublimation32. In order to participate on the power market a TSO gathers information about the RES feed-in, expected on the certain month. As already mentioned the appropriate forecasts (excluding wind power) are available in the long-term and therefore can be considered within delivery commitments as continuous supply blocks. However, at the present time around two thirds of RES-electricity received by individual TSOs consists of wind energy (Figure 2-7).

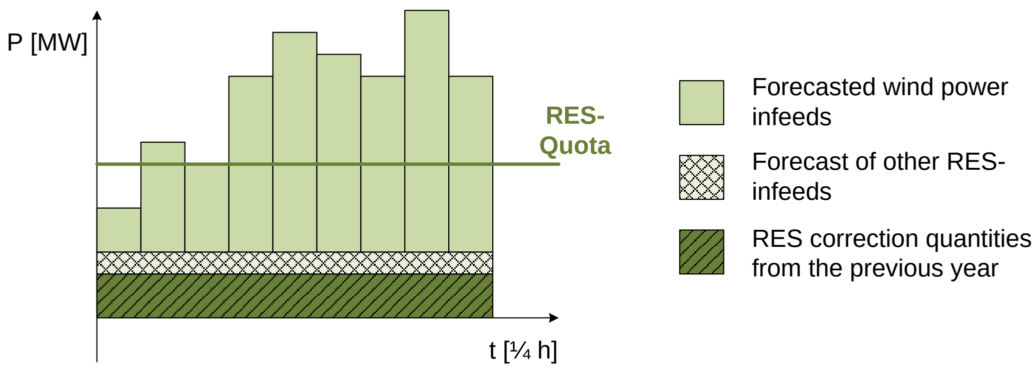

Figure 2-7: Composition of RES-quantities for the vertical equalisation

[32] (Germ.) EEG-Veredelung

The volatility of wind power feed-in makes it particularly difficult to forecast the expected level of renewable energy in each control area. Correspondingly the main costs of RES-sublimation fall on the proper prediction of wind power feed-in.

New nationwide equalisation scheme (valid from 01.01.2010)

With the innovation, becoming effective on 01.01.2010 the nationwide equalisation is partly changed. The changes are motivated through the transparency enhancement, simplification and further development the nationwide equalisation scheme. Additionally adopted AusglMechV prescribes that after the entry into force on 1 January 2010 the TSOs are no longer required to deliver RES-electricity to electric utility companies in form of a continuous supply. Instead of this all the RES-electricity purchased by the TSO before will be sold on a power market. Accordingly the nationwide equalisation scheme presented on Figure 2-4 changes as it is shown in Figure 2-8.

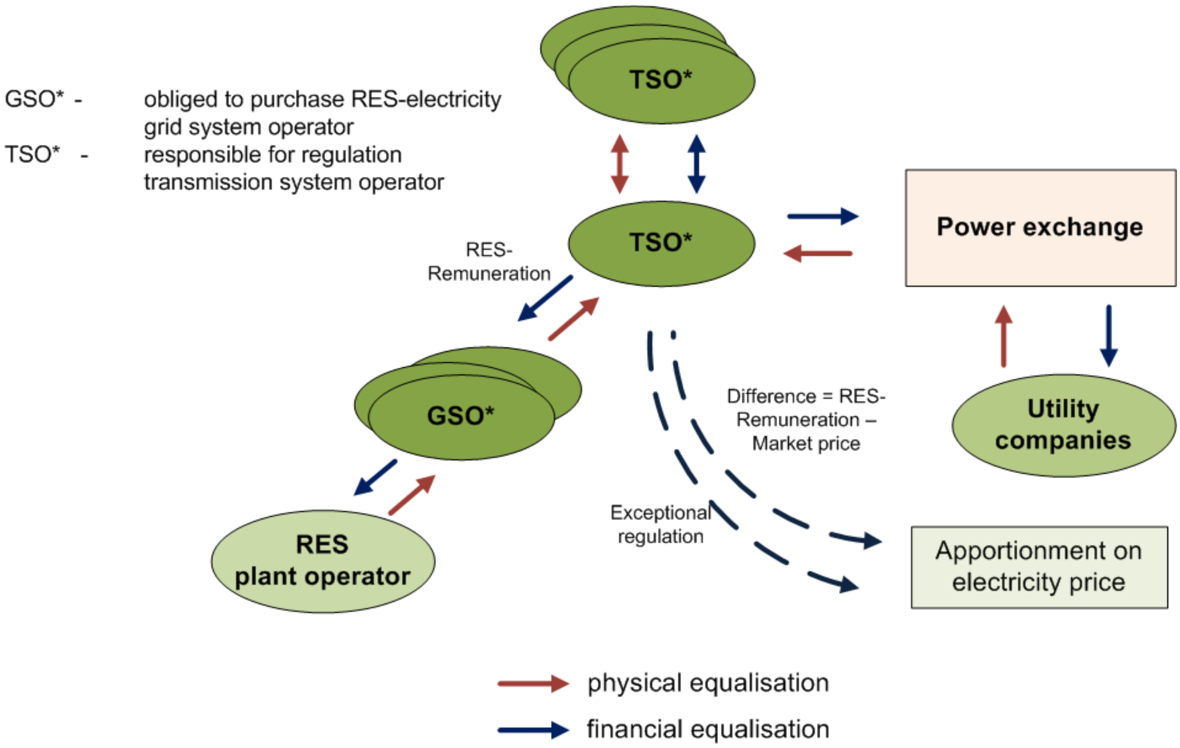

Figure 2-8: The German nationwide equalisation scheme (valid from 01.01.2010)

The innovation eliminates the vertical equalisation, and thus the costs of equalizing the differences between the predicted RES-quantities and delivery commitments of the TSO (costs for RES-sublimation). Instead of this all the RES-power received by TSOs within the nationwide balancing mechanism must be realized on the power market (in Germany, European Energy Exchange (EEX[33])). In this way the new regulation contributes to increasing of trading volume of RES-electricity, making the part of stochastic power sources in German energy mix higher. Since the HE is still required with the EEG2009, it became even more important for TSO **to know as exactly as possible the volumes of wind power** it has in its control area. Primarily the “sink”

[33] Since 2009 all short-term power commodities are traded on EPEX Spot SE (as a consequence of merge of EEX (Germany) and Powernext (France)). However, in this thesis the name “EEX” continues to be used for the purpose of convenience and common understanding.

control areas (that of Amprion and EnBW) are interested in high quality of wind predictions since they must market amounts of wind energy that exceeds their "own[34]" wind power generation in several times.

It is evident for now, that the changes in power policy together with corresponding electricity legislation altered the traditional role of a TSO as of provider of system services. As unbundled unit within the RES-equalisation scheme a TSO becomes a market player. The next section describes in more details the peculiarities of TSO's market participation and identifies further boundary conditions of the optimization of its market behaviour.

2.3 TSO as a market player

As mentioned jut now it is important to differentiate between two roles of a TSO. On the one hand a TSO is a provider of system services within its responsibilities regarding network stability. On the other hand, being a core participant of RES equalisation system, it is obliged to sell all the RES-power obtained on the power market. These two roles are technically and economically unbundled in accordance with §§6-10 of the EnWG. Figure 2-9 illustrates this principle.

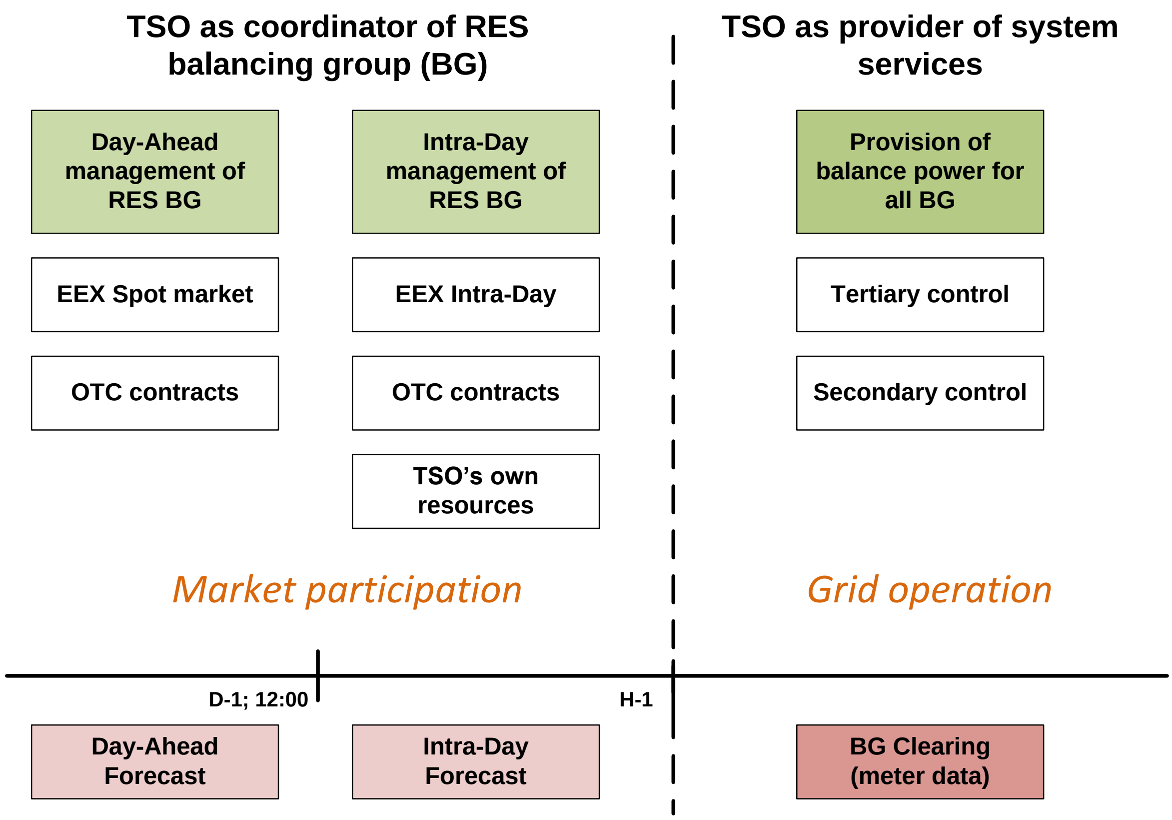

Figure 2-9: Differentiation of TSO's role as RES balancing group coordinator

[34] Reminder: TSOs do not own any generation units, the term „own" is used to characterize the wind power generation in the respective control area

Within the responsibility of the coordinator of a RES balancing group (RES-BG[35]) a TSO must overtake the role, which is similar to the tasks of a *market trader* having a wind power as a trading object. Since wind power does not belong to conventional power market products it is important to understand how its special features can influence a TSO's energy market participation.

Wind power has high investment costs and fairly low variable costs. Because part of the variable costs consists of annual fixes expenses, such as insurance and regular maintenance, the marginal running costs are seen to be even lower.

Therefore wind power is expected to **influence prices in the power market** in two ways. First, wind power enters the power market close to the bottom of the supply curve (due to mentioned low marginal costs). This, in turn, shifts the supply curve to the right, resulting in a lower market clearing price (depending on the price elasticity of the power demand). If there is no congestion in the transmission of power, the system price of power is expected to be lower during periods with high winds compared with periods with low winds [29]. Figure 2-10 shows an example with this so called "merit-order effect" of wind power trading for the case of one hour with inelastic power demand.

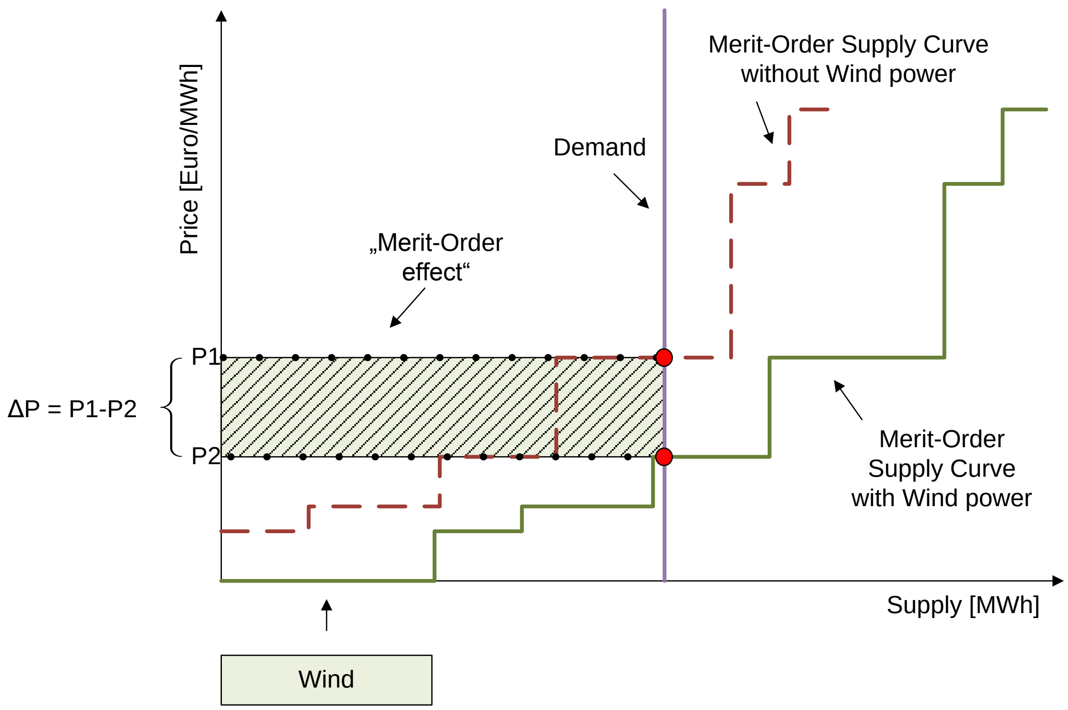

Figure 2-10: "Merit-Order effect" of wind power trading

[35] (Germ.) EEG-Bilanzkreis. In general a BG consists of any number of feeding and/or withdrawal points (nodes) within a TSO control area. In the balancing group the equilibrium between the feed-in from the assigned feeding points and deliveries from other balancing groups on the one hand (procurement) and the withdrawals of the assigned nodes together with deliveries to other balancing groups on the other hand (delivery) must be secured at any time [8]. In the RES-BG exclusively acquisitions and deliveries of renewable energy are summarized. That distinguishes RES-BG from the general definition.

Second, there may be congestion in power transmission (e.g. between TSOs' control areas), especially during periods with high wind power generation. Thus, if the available transmission capacity cannot cope with the required power export, the supply area (control area) is separated from the rest of the power market and constitutes its own pricing area [32]. With an excess supply of power in this area, conventional power plants have to reduce their production, because wind power normally will not be able to limit its power production. In most cases, this will lead to a lower price in this subarea [29].

In Western Denmark, characterized by a high share of wind power production, there have been several production hours during the night with a day-ahead power market price of zero. This reflects the fact that the relatively low load existing in these hours plus the scheduled interchange could be entirely supplied by wind power generation, and production from conventional plants which cannot be reduced due to system stability constraints and the need for heat production from combined heat and power plants [30].

Since the introduction of negative prices on the EEX (28.04.2008), the outcome of an auction can have good chances to result in minus values at calculation of market clearing price (as on 22.12.2008, 4-5h, price on the EEX -101€/MWh [31]). It would mean that the German TSO as supplier must pay for the buy-out of its wind power quantities.

It is obvious for now that a German TSO acts as a **price taker** on the power market and had no opportunity to drive up the prices with its wind power quantities. Due to its privileged status in Germany all the RES-energy a TSO receives must be accepted by the market and since wind energy has quite low marginal costs it will be certainly among the bidders admitted for dispatch. The advantaged dispatch right of RES feed-in is additionally supported by German legislation. In accordance with Part 3.1.1., No. (20) of "Benchmarks on the opening of the market segment REA processing [34]), a TSO must bid the obtained RES-amounts as **an unlimited order**, i.e. it bids the power quantity without a specification of the price.

As market trader within the nationwide equalisation scheme a German TSO is obliged to further legislative regulations, which limit its trading autonomy in a significant manner. Thus, i.e. it has no possibility to sell the wind power it has in its control area on the so-called over-the-counter (OTC) electricity market. Instead of this, the trading form of energy exchange, as a transparent one, is prescribed to be used for RES (wind) power trading. According to §2 Abs.2 of the AusglMechV the TSO is allowed to market the purchased RES-energy **only on a day-ahead and intraday spot markets** of the EEX.

Further, in contrast to conventional market participants (i.e. generation companies, electric utilities, traders) that can choose any of market products, the EEX provides for its users (see Figure 2-11[36]), German TSOs are only permitted to dispose the available wind power quantities **in form of hour contracts** (§2, §11 of AusglMechV; Part 3.1.1., No. (18) of "Benchmarks on the opening of the market segment REA processing[37]" [34]. These unlimited hour contracts must be submitted **till 12 a.m.** of the current day for the day ahead. Consequently a TSO has only a short time horizon to make a decision concerning the trading volume.

[36] Own scheme, based on [33]
[37] (Germ.) Eckpunkte der Ausgestaltung der Öffnung des Marktsegmentes EEG-Veredelung

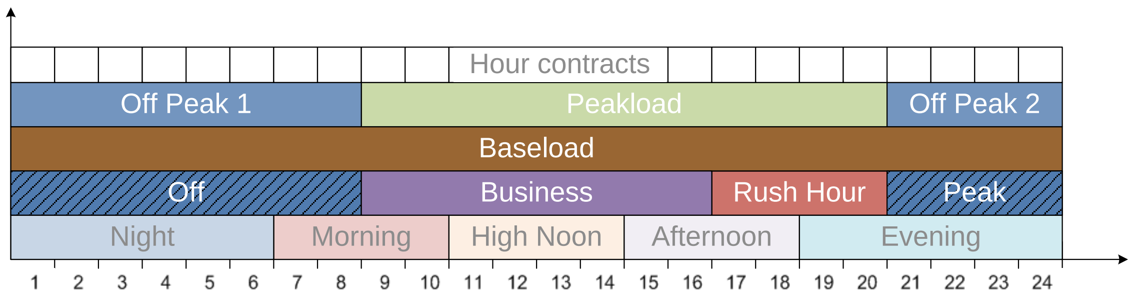

Figure 2-11: Electricity products on the EEX

In order to place a bid on the power market a TSO must have a clear view of availability of its power volumes. Since it has no power plants in its ownership (due to unbundling restrictions), the only information resource it can use for power scheduling is **wind power forecast.** Figure 2-12 presents the general decision situation for a TSO's operator.

The first wind power forecast a TSO receives is available at 8 a.m. on the day before the actual delivery. In the previous regulatory framework (EEG2004) a TSO had to compare the forecasted values with the RES-Quota in order to sublimate the differences between these two rates.

If the forecast was higher than the TSO's delivery commitment in a particular hour, then the difference for that hour on the following day was sold. If the forecasted value was below the value of the RES delivery to the utilities, then the difference was bought [27].

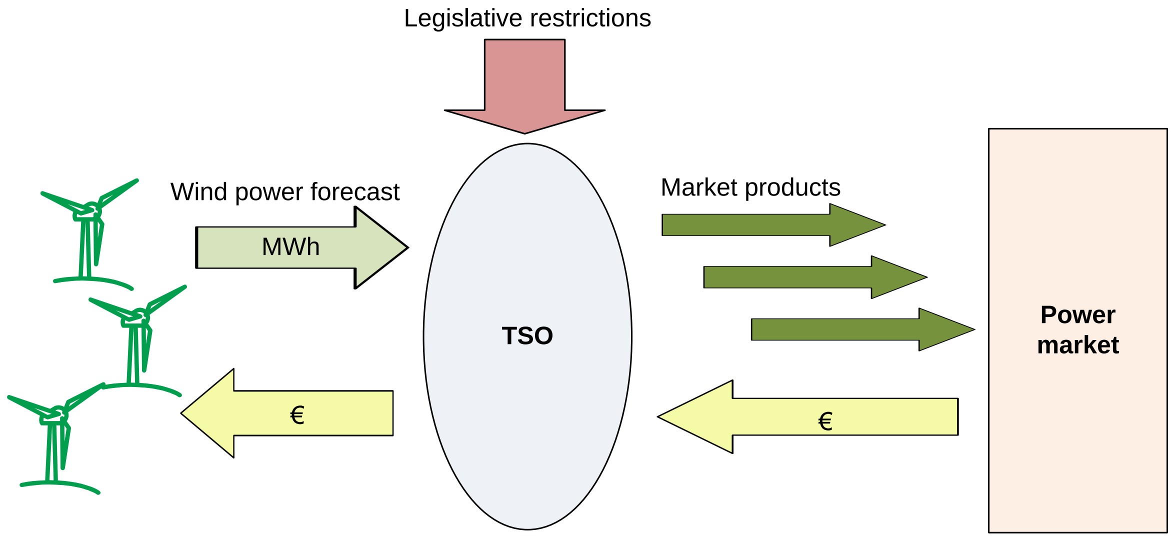

Figure 2-12: General scheme of TSO's market performance

This process is illustrated by an example of the wind energy feed-in and the delivery commitment on 12.07.2007[38] in the control area of tps (Figure 2-13).

[38] This particular day was chosen not because of its special characteristics but to illustrate the principle of TSO's market operation

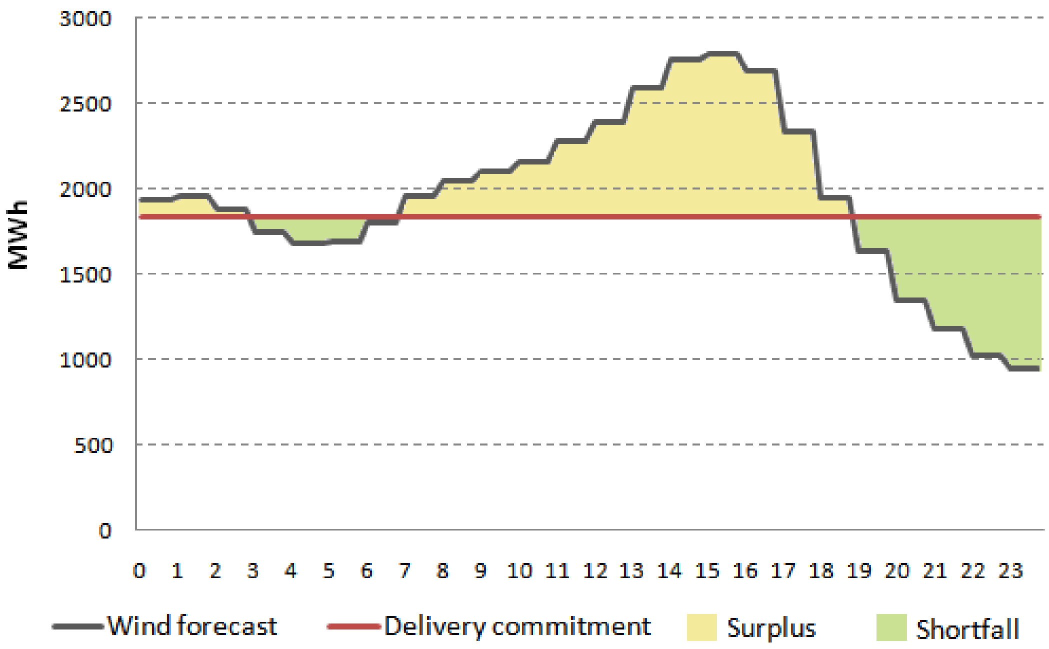

Figure 2-13: Day-ahead sublimation (regulation till 01.01.2010)

According to these scheme a TSO stood either on behalf of supplier (during periods of selling the additional quantities) or on the demand side (during periods of purchase) of the power market.

With the elimination of the vertical equalisation through the new regulation (EEG2009), the necessity of RES-sublimation is abolished and a TSO acts now only on the one side of the power market - it joins the ranks of power market supplier (Figure 2-14).

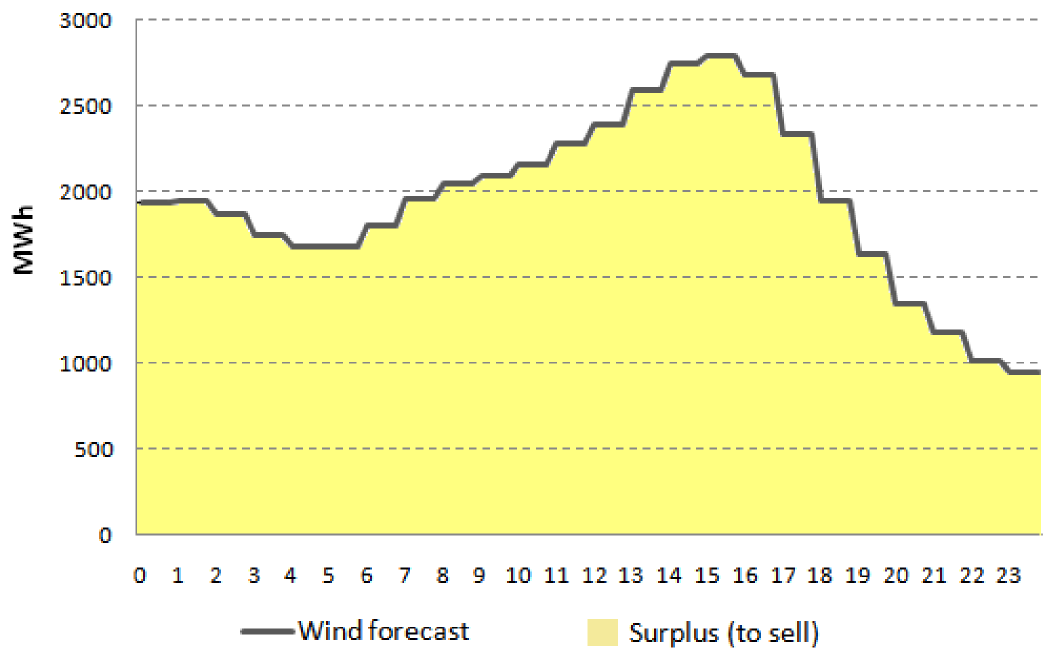

Figure 2-14: Day-ahead marketing of wind power

It is obvious that with this change in REA legislation the volumes of wind power that are marketed on a German power market are escalated from several hundreds of MW to several thousands.

Under these circumstances it is even more important to poses reliable information about quantities of wind power a TSO has on its disposal. Therefore a key factor for the successful market performance of a TSO is the **accuracy of the wind power forecast**.

The next Subchapter analyses the current forecasting tools used by German TSOs and describes the natural limits in wind power prediction.

2.4 Wind power trading. Need of forecast

Before analyzing wind power prediction it is important to understand the nature of wind power generation. Being a direct function of wind speed, wind generation is, in contrast to conventional generation systems, not easily dispatchable. Fluctuations of wind generation thus receive a great amount of attention. Variability of wind generation can be regarded at various time scales. First, wind power production is subject to seasonal variations, i.e. it may be higher in winter in Northern Europe due to low-pressure meteorological systems or it may be higher in summer in the Mediterranean regions owing to strong summer breezes. There are also diurnal cycles, which may be substantial or not, mainly due to thermal effects. Finally, fluctuations are observed at the very short-term scale (at the minute or intra-minute scale). The variations are not of the same order for these three different timescales. Managing the variability of wind generation is the key aspect associated to the optimal integration of that renewable energy into electricity grids.

Since wind power depends largely on meteorological conditions (especially on the magnitude of wind speed), it is of particular difficulty technically as well as economically to integrate these quantities into power market. The lack of exact predictability leads to overestimation/under-estimation of wind power quantity on the day-ahead market. Assuming periods of high wind that not occur results in non-commitment of some generations or imports and scheduling of more expensive generation in real-time. Another case of an under forecast of wind generation could lead to over-commitment of generations or imports and undesirable availability of cheaper resources in real-time.

This following section is dedicated to the analysis of existing forecasting methods and the sources for their inaccuracy.

2.4.1 General overview of existing wind power forecasts

While considering the modelling of wind behaviour it is very important to distinguish between the time horizons to forecast. There are several types of application of forecasting tools dependent on different prediction horizons:

- *Very short-term*. This type of wind power forecast (WPF) can be used for optimization of the scheduling of the conventional power plants (i.e. economic dispatch). The time horizon range is a few hours, but there is no unanimity for the number of hours (some authors propose the time horizon 0-6 hours [36], other – 3-10 hours [37]). The applications of this type remain marginal since only few on-line models of them are met today in island or isolated systems (i.e. [38]).

- *Short-term*. The time horizon ranges from the very-short–term limit up to 48 or 72 hours. This time horizon is mainly interesting for trading in the day-ahead market, but can also be used for unit commitment, economic dispatch, dynamic security assessment [39], etc. Depending on various regulations on power markets there are several time horizons that could be interesting to predict. For example, in the Iberian Electricity Market (daily market), the electric energy sale bids for the next day must be presented before 10:00, and, therefore, a 38-hour time horizon covers the entire following day. In other countries, the period for presenting offers is different (e.g., in the United States, it ranges from 5:00 to 12:00), so the number of hours in the time horizon can also diverge [40]. **This thesis is concerned with the last time scale given by the day-ahead electricity market, from 0-24 hours, where time step is one hour**.

- *Medium term.* The time horizon ranges from the short-term limit to a limit of 7 days. These longer time scales would be interesting for the maintenance planning of large power plant components, wind turbines or transmission lines. However, the accuracy of weather predictions decreases strongly looking at 5-7 days in advance, and such systems are only just now starting to appear [43].

Table 2-3 provides an overview of the time horizon classifications and the potential application of each forecast class in operation and planning of power systems, as well as the usefulness for possible users.

Modern wind power prediction system providing forecasts for a time horizon of up to four or five days in advance typically use numerical weather predictions (NWP). Whether it is worth (regarding the effort and expense of getting hold of it) to include a NWP model is worth, depends on the horizon one is trying to predict.

Table 2-3: Wind power forecasting time horizons

Time horizons	GENCOs, TSOs as coordinator of RES BG, IPP, other market participants	TSOs as provider of system services
Very-short-term (up to 9 hours)	Intraday market	Ancillary services management
	Real-time market	Congestion management
Short-term (up to 48 (72) hours)	**Day-ahead market**	Maintenance planning of network lines
	Maintenance planning of wind farms	Congestion management
	Wind farm and storage device coordination	Day-ahead reserve setting
Medium-term (up to 7 days)	Maintenance planning of wind farms	Maintenance planning of network lines
	Maintenance planning of conventional generation	

Typically, prediction models using NWP forecasts outperform time series approaches after ca 3-6 hours look-ahead time [37]. Therefore, all models employed by utilities use this approach. Hence, all the information about the future, in particular the expected evolution of the wind field, is provided by the NWP. The national weather services but also private weather data providers offer a broad range of different NWP data which is suitable for wind power predictions. The meteorological data typically consists of wind speed and direction and sometimes temperature, pressure and humidity data from sensors on one or more “met towers[39]” within the wind power plant’s boundaries. However, in order to achieve a higher level of forecast skill it is necessary to utilize data from beyond the plant’s boundaries. Meteorological data from in situ sensors deployed and operated by government agencies have been a traditional source of data for WPF. These include sensors on surface-based met towers deployed mostly at airports and sensors carried aloft by weather balloons to provide information about the vertical profile of temperature, humidity, winds and pressure. The main problem with this data is that the spacing between measurements is too large (because of economic constraints) to adequately represent the small or even sometimes medium scale atmospheric features that are responsible for short-term variations in wind energy output. However, these in situ sensor networks map quite well most of the features that are responsible for most of the variability over 1 to 2 day-ahead time scales. Unfortunately, there are large areas (such as the oceans) where very little in situ data is gathered because of the cost of maintaining such systems in those environments. This means that data coverage is far from uniform and that some regions have a lot less data upstream than others. This often results in poorer forecast performance in some areas [36].

The key issue in WPF is to transform the given numerical weather data into the power output of a wind turbine. For this purpose two fundamentally different approaches, the statistical approach on the one hand and the physical approach on the other hand, have been developed in recent years. Both of them led to prediction systems which are scientifically as well as commercially successful. A recent overview can be found e.g. in [37], [40], [48]. To take a short overview of the latest publications on this field it is recommended by author to read [42].

- *Statistical approach*: the idea is to derive a relation between meteorological predictions, historical measurements, and generation output through statistical models whose parameters have to be estimated from data, without taking any physical phenomena into account.

- *Physical approach*: consists of several submodels, which together deliver the translation from the NWP forecast at a certain grid point and model level, to power forecast at the considered site and at turbine hub height. Every submodel contains the mathematical description of the physical processes relevant to the translation.

Statistical models use a set of empirical equations from a sample of predictor and predictand (the quantity to be predicted) data called a “training sample”. The form of the equations is dependent on the type of model that is used. Typically, the equations have numerical coefficients that must be determined. A modelling procedure uses an optimization scheme to select the coefficient values that yield the best relationship between the predictors and the predictand. The meaning of

[39] “Met towers” – meteorological towers, are the most common means for measuring the wind speed and direction at a site. Generally a met tower will have anemometers, wind direction vanes, temperature and pressure sensors, and other measurement devices attached to it at various levels above the ground.

"best" in this context depends upon what optimization criterion is employed. An example of optimization criteria is the lowest mean absolute error or the lowest mean squared error. Once the coefficients are determined from the training sample, the resulting equations can be used to produce a forecast by inserting the current values of the predictors and calculating the value of the predictand [36]. Statistical models combine then the input variables from NWP and measured data (SCADA) in a so-called "black-boxes" (see Figure 2-15), which typically include most of the artificial-intelligence-based models, such as Neural Networks (NNs) and Support Vector Machines (SVMs). Other types of models are the "grey-box" models, which learn from experience (from a dataset) and for which prior knowledge (such as diurnal variations) can be injected [40].

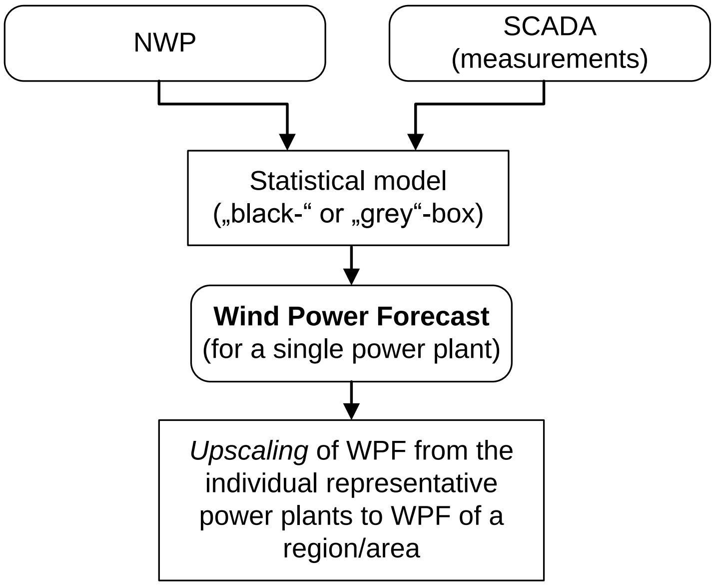

Figure 2-15: Main steps in the statistical approach

There are an enormous number of statistical models available for this type of an application. The most popular ones for atmospheric science applications are multiple linear regression (one very famous example is the system WPPT (Wind Power Prediction Tool) developed by the Danish Technical University [44], [45] and artificial neural networks (ANN, i.e. deployed by IWES [40] [46], a system which provides forecasts for a number of German TSOs [47].

If only one wind farm is to be predicted, then the model chain stops here (maybe adding the power for the different turbines of a wind farm while taking the wake losses into account). Since usually, users of WPF want a prediction for the certain area or region (since they service that), the upscaling from the single results to the area total is the last step. If all wind farms in an area would be predicted, this would involve a simple summation. However, since practical reasons[41] forbid the prediction for hundreds of wind farms, some representative farms are chosen to serve as input data for an upscaling algorithm. Helpful in this respect is that the error of distributed farms is reduced compared to the error of a single farm [37].

[40] http://www.iwes.fraunhofer.de/

[41] Forecasting the output of each single wind farm in a region/country can be very expensive and even prohibitive, as far as data management and computer effort (particularly for the statistical approach) are concerned [41].

In the case of physical approach the basic problem to be solved is the transformation of the wind speed given by the weather service on a coarse numerical grid to the on-site conditions at the location of the wind farm. This involves two important steps: the horizontal interpolation (downscaling) from the grid points to the coordinate of the turbine and the transformation of the wind speed from the height provided by the NWP, e.g. 10 m or 100 m, to the hub height as illustrated in Figure 2-16.

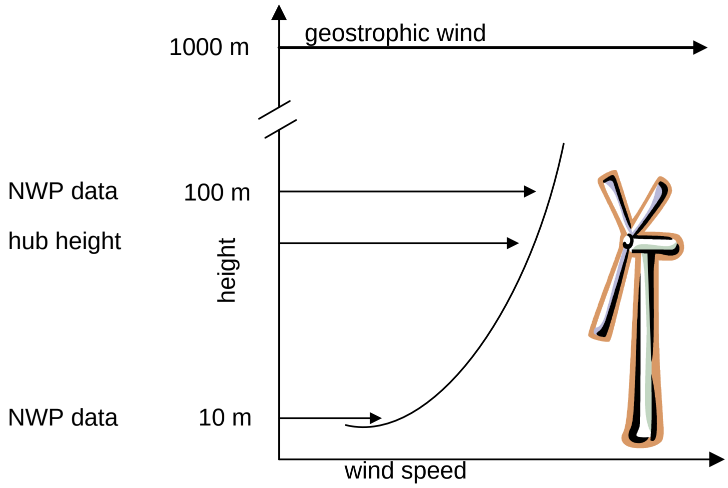

Figure 2-16: Transformation (scaling) of wind speed and direction to the hub height (adapted from [47])

For this purpose methods from boundary layer meteorology are applied to calculate the vertical wind profile for individual forecast situations. In the second step the corrected wind speed is plugged into the corresponding power curve to determine the power output [47]. Depending on forecast horizon and availability, measured power data can be used as additional input. In most cases, actual data is beneficial for improving the residual errors using Model Output Statistics (MOS) [48], see Figure 2-17.

There are some WPF systems that combine the two approaches in order to join the advantages of both and thus improve the forecasts. The fundamental concept is that if the errors in the forecasts produced by the different methods are unbiased and have a low degree of correlation with one another, the random errors from the individual forecasts will tend to offset each other, with the result that a composite of the forecasts will have a lower error than any individual forecast. If all of the input forecasts are highly correlated the impact of ensembling will be minimal. This means that the underlying forecast methods must be quite different in how they construct the relationships between the raw observational data and their forecasts or the type or amount of input data going into the methods must be significantly different [36].

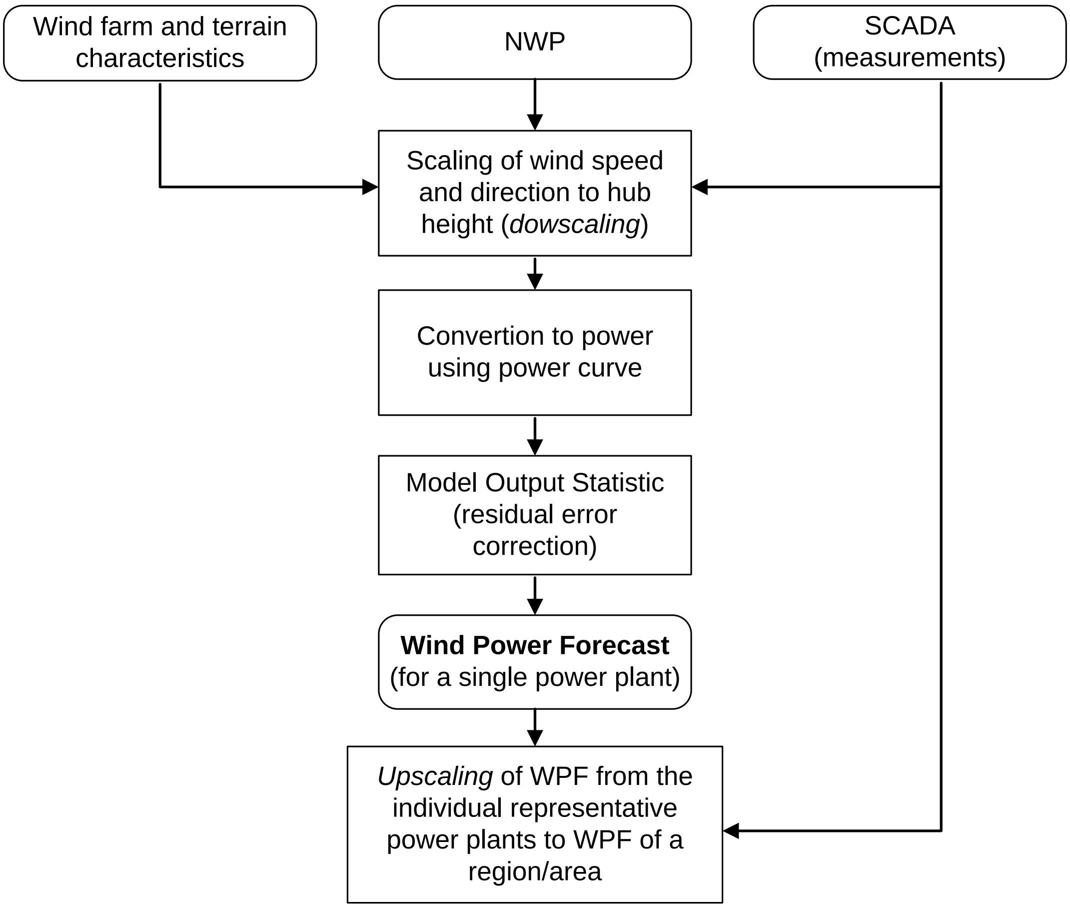

Figure 2-17: Main steps in the physical approach

There is no public information about what forecast models are used by particular TSOs exactly. However, according to the references of some providers of WPFs their products are in use by German TSOs and GSOs. A WPF, that a particular TSO finally applies, is then a meta-prognosis made of several WPFs. The weighting of individual forecasts is continuously checked and updated. On the next day the ex-post measurement data is available and therefore it is possible for a TSO to compare the forecasted and "real-time" values.

Table 2-4 provides an overview of these providers as well as of their products (adapted from [42]).

A WPF, that a particular TSO finally applies, is then a meta-prognosis made of several WPFs. The weighting of individual forecasts is continuously checked and updated. On the next day the ex-post measurement data[42] is available and therefore it is possible for a TSO to compare the forecasted and "real-time[43]" values.

[42] Online estimation

[43] "Real-time" values are referred as the extrapolated actuals of wind power feed-in, received from online measurements of representative wind farms (online estimation)

Table 2-4: Overview of Operational and Commercial WPF Systems available for German TSOs

Model	Developer	Key Feature
WPMS [26],[46]	IWES	It calculates the current power for all wind farms by using the measurements of reference wind farms (on-line monitoring); provides day-ahead and short-term wind power forecasts for single wind farms, control areas, and subregions; and functions as a multi-NWP that combines the forecasts of three different NWP models from different providers or a multi-scheme ensemble weather forecast system (MSEPS) that uses the forecasts of different members of the ensemble.
WEPROG [52]	WEPROG[44]	There are two main models: a weather prediction system running every 6 hours and a power prediction system that uses on- and off-line supervisory control and data acquisition (SCADA) measurements. In the first model, a multi-scheme ensemble prediction limited-area NWP model produces 75 different forecasts (ensembles), which forecast uncertainty and improve forecast accuracy.
SOWIE	Eurowind GmbH[45]	This model uses high-resolution, three-dimensional wind and temperature forecasts as inputs, together with a database of all German wind energy turbines; it provides uncertainty estimation and regional forecasting.
Previento [53]	University Oldenburg/EMSYS[46]	This model provides local refinement of the NWP forecasts; it generates wind power curve modelling, including wake effects; it provides regional forecasting and uncertainty estimation.

2.4.2 Forecast error and its consequences

However, there are clearly natural limits in the quality of a WPF. That is because of high sensitivity to initial conditions, which a WPF is prone to.

In the early 1960's using a simple system of equations to model convection in the atmosphere, Edward Lorenz, an MIT meteorologist, ran headlong into "sensitivity to initial conditions". In the process he sketched the outlines of one of the first recognized chaotic attractors. In Lorenz's meteorological computer modelling, he discovered the underlying mechanism of deterministic chaos: simply-formulated systems with only a few variables can display highly complicated behaviour that is unpredictable. Using his digital computer, he saw that slight differences in one variable had profound effects on the outcome of the whole system. This was one of the first clear demonstrations of sensitive dependence on initial conditions. He also appreciated that in real weather situations, this sensitivity could mean the development of a front or pressure-system where there never would have been one in previous models. In his famous 1963 paper Lorenz

[44] http://www.weprog.com
[45] http://www.eurowind-gmbh.de
[46] http://energymeteo.de

picturesquely explains that a butterfly flapping its wings in Beijing could affect the weather thousands of miles away some days later. This sensitivity is now called the "butterfly effect" [49].

This Lorenz model is presumed to be a paradigm for deterministic chaos and indicates one important problem for practical usage of wind power: **A reliable prediction of wind relations at a certain place even considering actual measurements from numerous grid points is only possible for some hours, maximal for something more than one day**.

In accordance with [48], [51], **the largest source of error** in a typical short-term prediction model is the **NWP input**. Within the weather forecast, the largest error possibilities are due to

- the (limited) horizontal and vertical resolution of the model,
- the number of weather observations used (especially upstream)
- and the quality of the data assimilation,
- plus the actual model physics as well.

The limited horizontal resolution is especially important in complex terrain, which is why wind farms in mountains and to some extent, near-shore conditions, show typically higher errors than wind farms in easy terrain [51]. Additionally, typical error sources can be the power curve modelling and modelling of wind-to-power conversion process.

Besides of modelling errors, reliability of input data is crucial for operational application since, if some error appears in the process, the short time frame does not permit human intervention. Typical errors in the process can be due to [51]:

- Failure of SCADA system or communication system with the wind farm.
- Failure of NWPs delivery.
- Failure of wind power prediction models
- Other sources of problems may be security problems, database problems, bugs in the software, problematic graphical user interfaces etc.

For this, it is needed to have adequate IT infrastructure and redundant servers to meet high reliability requirements.

Such forecast errors can result in hundreds of MW needed to be purchased/sold additionally (Figure 2-18). If they could be detected (e.g. by means of more accurate forecast) quite early (e.g. till 75 minutes to contract execution), there is a possibility to balance the differences within the intraday trade. However, according to the historical data available to TSOs, the prices on the intraday market are usually much more unfavourable (for purchase – much more expensive, for selling – much cheaper) than on e.g. day-ahead market or in comparison with longer-term contracts a TSO may have with conventional power supplier with short-times power disposability (wind reserves). If the possibility of intraday trading is not given, the deviations are equalized by using balancing energy, for which TSOs must have guaranteed continuous full availability in advance.

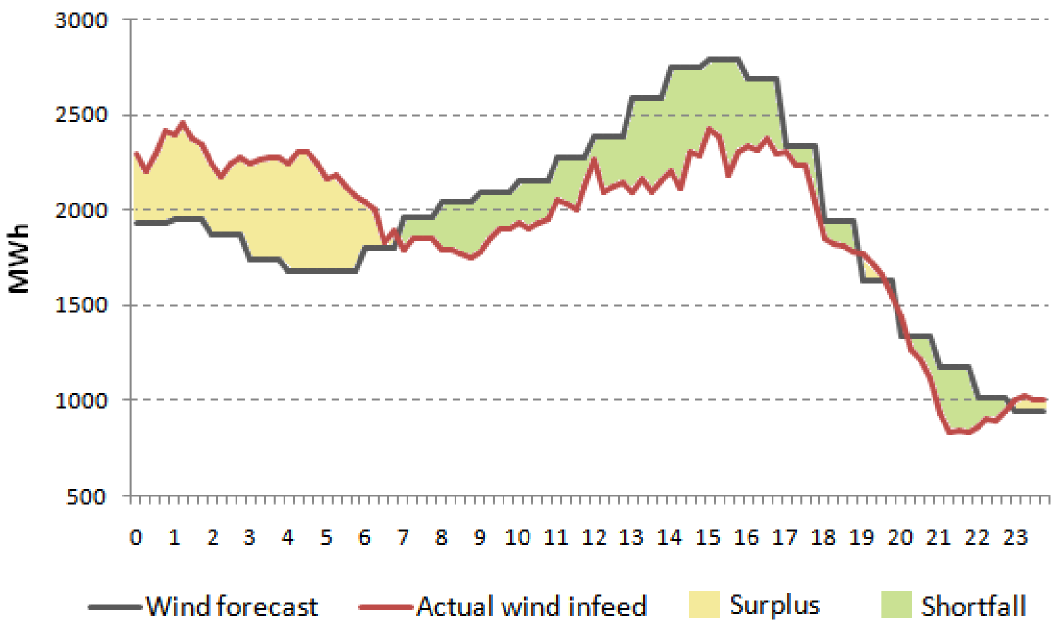

Figure 2-18: Additional sublimation quantities due to the day-ahead forecast error

Unforeseen fluctuations of wind power amounts mean a challenge for market participants, and first of all for TSOs that are responsible of cost-effective operation of RES-BG, not to mention maintaining of the nominal frequency in the grid. The last mentioned task refers to TSO's role of provider of ancillary (system) services (see Figure 2-9) and can be quite difficult in case of situations when substantial part of wind farms in a supply area is switched off for security reasons during a storm. Control power applied to compensate such wide-ranging outages is provided through an activation of additional fossil fuel driven plants [35]. As a result substantial environmental costs are caused by undesirable CO_2 emissions. Table 2-5 gives an overview of these and other costs connected with stochastic nature of wind power.

Table 2-5: Costs and influencing variables of RES equalisation process

TSO Responsibility	Expense factor		Influencing variables
RES equalisation (sublimation)	Trading		Forecast of the total RES feed-in
			Correlation RES feed-in with spot price
			Activation strategy of the wind reserve
	Wind reserve	Procurement	Forecast of the total RES feed-in
			Individual activation strategies
		Activation	Deviation of the RES forecast
			Individual activation strategies
	Service agreement		Operating expenses
	Operating costs of RES balancing group		Forecasting costs, etc.
			Administration and personnel costs

Table 2-5. Continuation.		
TSO Responsibility	**Expense factor**	**Influencing variables**
Ancillary services	Wind caused control power	Online estimation error
		Short-term fluctuations in RES balancing group
		Compensation with load and generation
	Balancing energy	Online estimation error
		Correlation of RES balancing group with the control area

In any of these cases[47] these adjustment measures result in higher costs for a TSO and therefore in higher electricity tariffs for final customers (Figure 2-19).

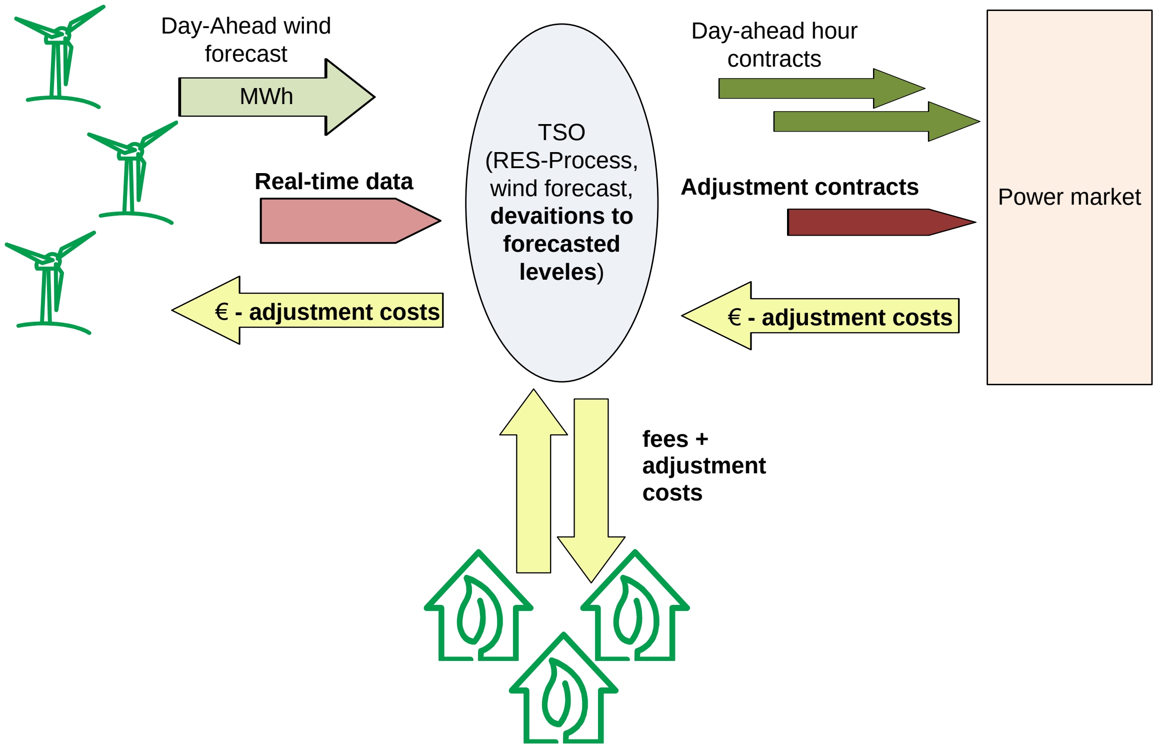

Figure 2-19: Adjustment contracts and their consequences

In order to understand what amounts these adjustment costs can have, Figure 2-17 is presented. It shows the costs for capacity provision for control power and for its application in the control area of 50Hertz Transmission GmbH[48] for the year 2009 [50]. These costs become due as a consequence of WPF's inaccuracy, which could not be covered through intraday power market or RES reserves. If one adds the costs for these two measures for overcoming the forecast inaccuracy as well, the values could have been even more.

[47] Derived from [64]

[48] The example of 50Hertz is chosen because it is the only TSO that made this information publicly accessible.

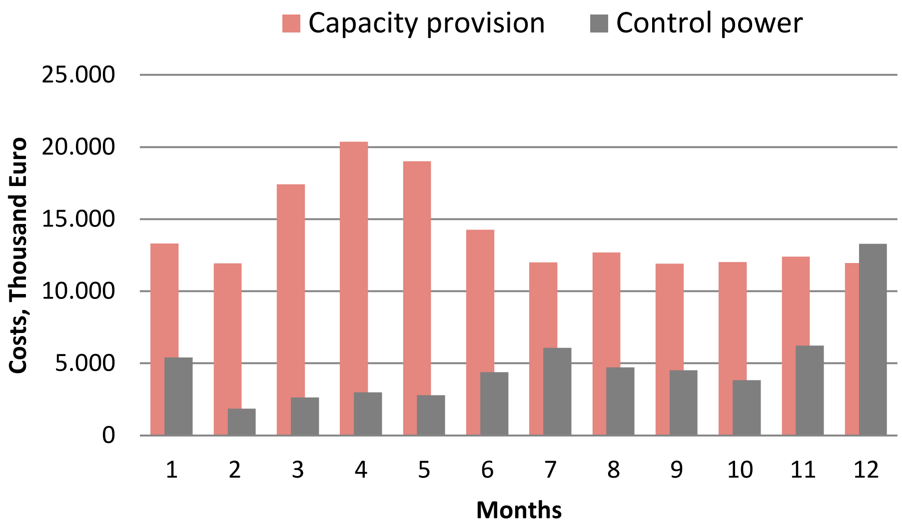

Figure 2-20: Additional costs due to forecast inaccuracy

The next section summarizes all the circumstances of a TSO position in the nationwide equalisation scheme and defines the boundary conditions for the optimization of its market performance.

2.5 Boundary conditions for optimization of TSO's market behaviour

Previous Subchapters have shown that traditional obligations of a German TSO as of provider of system services have changed significantly. Being involved in the nationwide equalisation scheme a TSO has now tasks that are quite new for him and where it does not have years of successful operation. Further boundary conditions dictated by an electricity market and specifications of the trading object (wind power) limit the optimization possibilities for TSO's market performance. Figure 2-21 reviews the environment a TSO must work within.

Being obliged to purchase, transmit and pay for RES-energy in advance a TSO must overtake all the risks combined with stochastic nature of the obtained amounts. Due to regulations of the HE some TSOs must market wind power volumes that exceed their own generation capacities in many times. In correspondence with the unbundling restrictions a TSO does not own any generation units that could equalize the volatility of received wind power feed-in.

Becoming a market player a TSO has no rights to exploit the whole palette of marketing possibilities since it must market the received wind power only in form of hour contracts with no specification of a price. In fact, the only leverage a TSO can use in optimization of its bidding behaviour is **the trading amount**. However, this value is determined through the WPF a TSO receives at 8 a.m. As long as a TSO receives the WPF as a service, it has no influence on the modelling assumptions and techniques used within these forecasts. It means it has no control over errors contained in the NWPs, SCADA, prediction models and must accept them as they are.

The only opportunity to discover whether its marketing decisions were right is given on the next day, when the “real-time” values (online estimation data) are available.

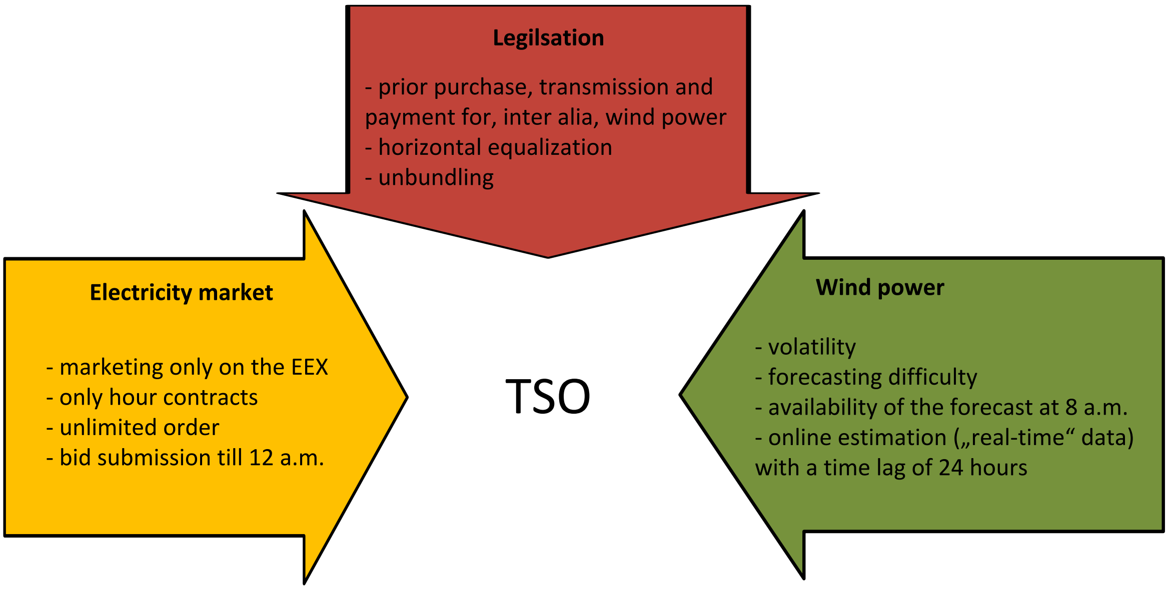

Figure 2-21: Boundary condition for optimization of TSO’s market performance

Becoming a market player a TSO has no rights to exploit the whole palette of marketing possibilities since it must market the received wind power only in form of hour contracts with no specification of a price. In fact, the only leverage a TSO can use in optimization of its bidding behaviour is **the trading amount**. However, this value is determined through the WPF a TSO receives at 8 a.m. As long as a TSO receives the WPF as a service, it has no influence on the modelling assumptions and techniques used within these forecasts. It means it has no control over errors contained in the NWPs, SCADA, prediction models and must accept them as they are (Figure 2-22). The only opportunity to discover whether its marketing decisions were right is given on the next day, when the “real-time” values (online estimation data) are available.

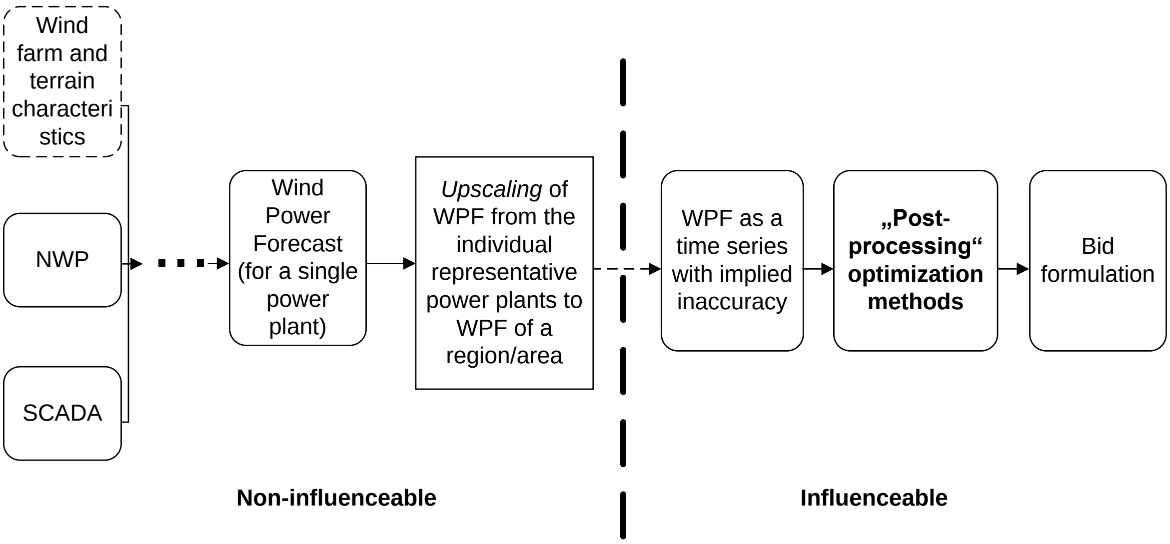

Figure 2-22: Optimization possibilities of a TSO. Non-influenceable and influenceable

Consequently **the only possibility to optimize a TSO's electricity market performance is to predict the forecast inaccuracy of the WPF it receives**. Having no information about the internal modelling errors, the obtained prediction data must be assumed as an isolated time series with implied inaccuracy nature.

Moreover, since according to regulations on the EEX, a market bid must be passed on to the power exchange not later than 12 a.m., a TSO has only limited time (4 hours) at its disposition to evaluate the errors, the received WPF may contain.

These boundary conditions restrict the optimization measures a TSO can take in order to improve its market behaviour. It means in particular that the optimization methods that are to be developed within this thesis are subjected to fulfill some **requirements**. Thus the methods to be used for optimization of TSO's market behaviour must:

- rely on limited input data. In fact there are no NWP forecasts available to the operator or specifications which SCADA data is used;
- the only data source the operator can use is these two time series described before: day-ahead WPF (weighted WPF from several providers) and ex-post "real-time" values (therefore the methods could be defined as "post-processing" optimization methods, see Figure 2-22);
- not claim much time for calculations. It must be rather a simple model, which is easy to use. A possibility to change the initial conditions must be ensured;
- the calculations must consider the current RES legislation (include regulations of the HE);
- the model must outperform the initial day-ahead forecast.

These boundary conditions were considered for the search of suitable optimization methods, and, as it is usual in modelling, in order to overcome these limitations some assumptions about input data and simulation object were made.

Chapter 3

Optimization methods

In addition to considerations from the previous chapter a typical TSO's decision making problem is presented and must be optimized:

A TSO receives a WPF. After the exchange of energy amounts within the HE the exact amount of expected wind power on the nest day in its control area is known. Based on this input information it must submit the market bids for each hour of the next day (day-ahead trading). On the next day it receives actualized "real-time" data – the wind power quantities that are really occurred in its control area. Due to forecast errors discussed above some differences between the forecasted and "real-time" data are revealed. These differences must be balanced out by means of RES-reserves, control energy or intraday trading. The greater the difference, the more costs a TSO must take. It is obvious, that if these deviations are reduced, more costs can be saved and thus the performance of a TSO on the power market can be optimized. Hence better forecasting techniques must capture this problem.

3.1 Motivation

In fact, this task can be solved using various techniques, i.e. linear autoregressive models (i.e. ARMA[49] as it is i.e. in [59]) or non-linear time series models (i.e. ARCH[50], as it is for load forecasting in [60]). These techniques could predict the next value of a certain time series based on known past events. However, the task of this thesis was not to predict the next forecasted value. This information is actually already given within the 24-hours-forecast a TSO obtain. It was more important to support an individual operator in its decision making: having this predicted

[49] Auto-regressive moving average models
[50] Auto-regressive conditional heteroscedasticity

value, what should be made in order to hold the difference between this and the "real-time" value, which is not known at the moment, as small as possible.

Such kinds of decision making situations can be assumed to be a Markov decision process (MDP). This kind of process, named after Russian mathematician Andrey Markov, provide a mathematical framework for modelling decision-making in situations where outcomes are partly random (a TSO has no influence on "real-time" values it receives) and partly under the control of a decision maker (by modifying its market bids a TSO can influence the difference between forecasted and real values). MDPs are useful for studying a wide range of optimization problems solved via dynamic programming and reinforcement learning.

The core problem of MDPs is to find a policy for the decision maker: a function π that specifies the action $\pi(s)$ that the decision maker will choose when in state s. This problem definition fits best the situation a TSO has each day: it needs a policy that support it to choose an action that minimize the difference between its market bid and "real-time" value it receives afterwards.

Since a TSO does not know whether a WPF it receives over- or underestimates the real wind power feed-in, it does not have any defined policy for its market bid submission. It must first discover, which decisions (market bids it makes) lead to what "results" (differences in comparison with the "real-time" values.) This type of interaction with its environment can be best described as the reinforcement learning – a TSO, taking an action in a certain time step, receives an answer from its environment in form of "real-time" values. In dependence on the differences between the action and answer (reward) the next action (and since confidence in the WPF) is reinforced (small difference) or weakened (big difference).

For comparison, in the standard reinforcement learning model an agent interacts with its environment (Figure 3-1). This interaction takes the form of the agent sensing the environment, and based on this sensory input choosing an *action* to perform in the environment. The action changes the environment in some manner and this change is communicated to the agent through a special signal from the environment called the *reward*. Unlike the sensory information, which may be a large feature vector, or the action, which may also have many components, the reward is a single real-valued scalar, a number. The goal of learning is the maximization of the cumulative reward received over time [71], [72].

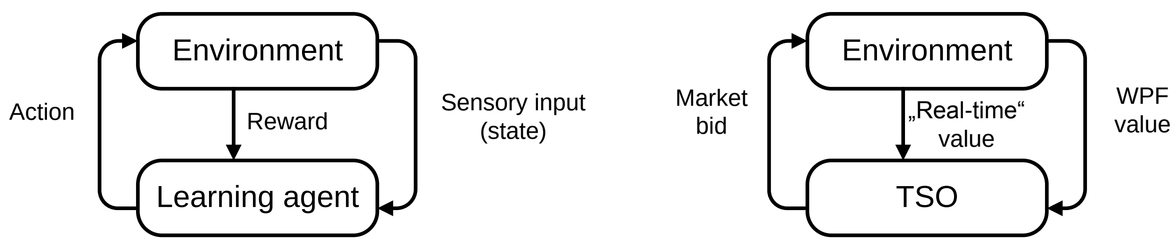

Figure 3-1: The Reinforcement Learning Problem (left) and the TSO's decision making problem (right)

Inspired by related psychological theory, in computer science, reinforcement learning is a sub-area of machine learning concerned with how an agent has to take actions in an environment so as to maximize some notion of long-term reward. Reinforcement learning algorithms attempt to find a policy that maps states of the world to the actions the agent has to take in those states. In economics and game theory, reinforcement learning is considered as a boundedly rational interpretation of how equilibrium may arise.

The environment is typically formulated as a finite-state MDP, and reinforcement learning algorithms for this context are highly related to dynamic programming techniques.

Brian Arthur [54] was among the first economists to suggest modelling agent behaviour using reinforcement-type learning algorithms and to calibrate the parameters of such learning models using data from human subject experiments. Roth and Erev [55] and Erev and Roth [56] go beyond Arthur's study and examine how well reinforcement learning algorithms track experimental data across various different multi-player games that have been studied by experimental economists. Varieties of reinforcement learning algorithms have become a mainstay of agent-based modelling because they accord with Axelrod's KISS principle[51]. Other attractive features are the low level of history-dependent rationality, and relatively few parameters [58].

There are numerous examples of the use of these models in electricity market models. Nicolaisen et al. [59] use Roth-Erev-type reinforcement learning to model buyer and seller price-quantity decisions in a computational model of the wholesale electricity market. Bower and Bunn [62] use a modified version of the same algorithm for price forecasting in bilateral trading negotiations within the model of UK electricity market. Finally, Sun and Tesfatsion [63] apply reinforcement learning to model suppliers' behaviour in the USA electricity market model.

There is also a parallel and much more voluminous literature on reinforcement learning in the machine learning literature. See, e.g. Sutton and Barto [70] for surveys. A popular reinforcement learning model in this literature is Q-Learning [68], which is closely related to Bellman's approach to dynamic programming, but differs from the latter in being much less informationally demanding, e.g. the agent need not know the period payoff or state transition functions. Q-Learning algorithms involve on-line estimation of an evaluation function, denoted $Q(s,a)$, representing the maximum expected discounted sum of future payoffs the agent earns from taking action a in state s. Starting from some random initialization of values, estimation of the Q-function occurs in real-time using the history of states and payoffs earned by the agent form action choices in those states. To determine the action chosen, a probabilistic choice rule is used: action with higher Q-values for the given state s and the current approximation of the Q-function, are more likely to be chosen than the actions with lower Q-values. Thus Q-learning is learning an evaluation function mapping from states to actions, analogous to the policy function of dynamic programming. An advantage of Q-Learning over reinforcement learning algorithms presented

[51] The principle is derivated from the army slogan "Keep it simply, stupid" and implicates that simplicity in modelling presumptions may result in interesting findings about the investigated process . Robert Axelrod formulates it as follows: "Although agent-based modelling employs simulation, it does not aim to provide an accurate representation of a particular empirical application. Instead, the goal of agent-based model-ling is to enrich our understanding of fundamental processes that may appear in a variety of applications. This requires adhering to the KISS principle, which stands for the army slogan 'keep it simple, stupid" [57]

before (e.g. Roth-Erev algorithm) is that convergence results for Q-Learning can be proved under certain assumptions, e.g. for simple MDPs [58].

Applications of Q-Learning algorithms in modelling of electricity market are also widely spread. Harp et al. [65] use this approach for the optimal pricing bidding of generation companies dependent on customer acceptance of their generation rates. Assuming the node-pricing system of the USA, Yu et al. [66] consider a simple demand-side response model for formulating of Q-Learning state vector. In [67] the Q-Learning algorithm is used with the purpose of maximization of a supplier profit in the long-term and to satisfy the requirement of generation usage factor.

Concluding following characteristics of Q-Learning algorithm are best suitable to model the TSO's market behaviour:

- It is the natural tool for describing and simulating a system composed of behaviour al entities where individual behaviour can be characterized by if-then rules;
- It provides an optimal policy in long-term;
- It can be used in real-time using the history of states and payoffs (look-up table);
- There is no necessity to model the TSO's behaviour explicitly; the optimal policy evolves on its own during the training phase;
- Its convergence is proved for Markov-decision processes.

However, as every modelling tool, Q-Learning has also its drawbacks. In particular, the stochastic of the input data is not explicitly described. This volatility must be firstly learned. It means a certain waiting time for learning is necessary and an operator can not use this tool immediately, having i.e. only a pair of known "real-time" values. Furthermore, the underlying system is a dynamic one, i.e. it can change its statistical properties over time, e.g. due to seasonal fluctuations.

However, it will be shown that appropriate adaptation of the algorithm will allow overcoming the mentioned difficulties. In particular, in order to learn the wind volatility an optimal learning phase must last approx. few months. These historical values are normally available. Regarding the second point, the periodical re-initialization of the method is proposed. The details are presented in sections 3.3.2 and 4.2.

The second estimation method applied in this work is the Kalman filter (KF). Named after its discoverer R.Kalman [88], KF is probably the most famous estimator for dynamic systems. KF applications range from tracking the trajectories of celestial bodies till the forecasting of the prices of traded commodities. KF is an efficient recursive filter that estimates the state of a linear dynamic system from a series of noisy measurements. Simply speaking, it is used to remove the disturbance caused by the measuring instruments.

The Kalman filter is important because it may be applied in real time. That is, as each value of the time series is observed, the forecast for the next observation can be computed.

In contrast to the Q-Learning application, which suggests a policy to be followed; the Kalman filter predicts the current state (the forecasted level of wind power feed-in) better than the initial day-ahead forecast. In this way, the adjusted market bid can be submitted. Finally, the advantages of both models are gathered within a combined approach.

Following sections are dedicated to description of mathematical backgrounds of both methods.

3.2 Mathematical background

3.2.1 Q-Learning

The wide application of the Q-Learning algorithm is grounded through its simplicity to learn how to act optimally and because it imposes limited computational demands. It works by successively improving its evaluations of the quality of particular actions at particular states. The Q-Learning [68] is an incremental reinforcement learning (RL) method. It is a good representative for RL because it is simple, mathematically well founded, and widely used [69].

RL is learning what to do - how to map situations to actions - so as to maximize a numerical reward signal. An agent is not told which actions to take, but instead must discover which actions yield the most reward by trying them. In the most interesting and challenging cases, actions may affect not only the immediate reward but also the next situation and, through that, all subsequent rewards. These two characteristics - *trial-and-error search* and *delayed reward* - are the two most important distinguishing features of RL [70]. These and other features, listed below, make RL appealing:

- learning occurs through trial-and error experimentation with the environment;
- the feedback used for learning takes the form of scalar payoff – no explicit teacher, who offers the “correct answer” is required (unsupervised learning);
- little or no prior knowledge is required;
- RL is incremental and can be used online;
- RL architectures are extensible.

There are three fundamental parts of a reinforcement learning problem and since of a Q-Learning problem:

- the environment,
- the reinforcement function,
- and the value function

which will be described further in detail.

The environment

The environment is modelled as a MDP. At each point of time the agent directly observes the state of the environment and the effects of actions depend only upon the action and the current state.

Formally, a MDP is described by the tuple $(\mathcal{S}, \mathcal{A}, \mathcal{R})$, where $\mathcal{S}$ is the set of possible states, $\mathcal{A}$ is the set of possible actions, and $\mathcal{R}$ is the reward function. At each time, the environment occupies exactly one state from $\mathcal{S}$, and accepts one action from $\mathcal{A}$. $\mathcal{S}$ and $\mathcal{A}$ are usually assumed to be discrete and finite. Payoffs generated by the environment are determined by a reward function, $\mathcal{R}$, which maps state-action pairs into scalar-valued rewards ($\mathcal{R} : \mathcal{S} \times \mathcal{A} \rightarrow \mathbb{R}$) [69].

By "the state" whatever information is meant, which is available to the agent. The assumption is that the state is given by some pre-processing system that is nominally part of the environment. The issues of constructing, changing, or learning the state signal are unimportant for the current context, since the goal is to focus fully on the decision-making issues. In other words, the main concern is not with designing the state signal, but with deciding what action to take as a function of whatever state signal is available.

Ideally, a state should be a signal that summarizes past sensations compactly, yet in such a way that all relevant information is retained. This normally requires more than the immediate sensations, but never more than the complete history of all past sensations. A state signal that succeeds in retaining all relevant information is said to be *Markov*, or to have *the Markov property*. This is sometimes also referred to as an "independence of path" property or said to be a memoryless process because all that matters is in the current state signal; its meaning is independent of the "path," or history, of signals that have led up to it [69],[70]. The Markov property is fundamental to this model of the environment because it implies that knowledge of the current state is always sufficient for optimal control (i.e., to maximize the reward received over time). Thus, even though it may be possible to devise action-selection strategies whose decisions depend upon additional information (e.g., a history trace), these strategies cannot possibly outperform the best decision strategies that depend only upon knowledge of the current state [70].

Formally the Markov property for the reinforcement learning problem can be defined as follows. To keep the mathematics simple, the assumption about a finite number of states and reward values is made [70]. This circumstance makes it possible to work in terms of sums and probabilities rather than integrals and probability densities, but the argument can easily be extended to include continuous states and rewards. Consider how a general environment might respond at time $t + 1$ to the action taken at time t. In the most general, causal case this response may depend on everything that has happened earlier. In this case the dynamics can be defined only by specifying the complete probability distribution:

$$Pr\{s_{t+1} = s', r_{t+1} = r \mid s_t, a_t, r_t, s_{t-1}, a_{t-1}, \dots, r_1, s_0, a_0\}, \tag{3.1}$$

for all s', r and all possible values of the past events: $s_t, a_t, r_t, \dots, r_1, s_0, a_0$. If the state signal has the Markov property, on the other hand, then the environment's response at $t + 1$ depends only on the state and action representations at t, in which case the environment's dynamics can be defined by specifying only

$$Pr\{s_{t+1} = s', r_{t+1} = r \mid s_t, a_t\}, \tag{3.2}$$

for all s', r, s_t and a_t. In other words, a state signal has the Markov property, and is a Markov state, if and only if Eq. 3.2 is equal to Eq. 3.1 for all s', r and histories, $s_t, a_t, r_t, \dots, r_1, s_0, a_0$. In this case, the environment and task as a whole are also said to have the Markov property.

If an environment has the Markov property, then its one-step dynamics of Eq. 3.2 makes it possible to predict the next state and expected next reward given the current state and action. One can show that, by iterating this equation, one can predict all future states and expected rewards from knowledge only of the current state as well as would be possible given the complete history up to the current time. It also follows that Markov states provide the best possible basis for choosing actions. That is, the best policy for choosing actions as a function of a Markov state is just as good as the best policy for choosing actions as a function of complete histories [70].

The reinforcement function

As stated previously, RL systems learn a mapping from situations to actions by trial-and-error interactions with a dynamic environment. The "goal" of the RL system is defined using the concept of a reinforcement function, which is the exact function of future reinforcements the agent seeks to maximize. In other words, there exists a mapping from state/action pairs to reinforcements; after performing an action in a given state the RL agent will receive some reinforcement (reward) in the form of a scalar value. The RL agent learns to perform actions that will maximize the sum of the reinforcements received when starting from some initial state and proceeding to a terminal state [71]. In particular, the mapping procedure is as follows.

The agent is responsible for generating actions. At each time step it senses the current state, selects an action, and observes the new state and reward that result. Rewards are used as feedback for learning.

The agent's action choices are a stochastic function of the state, called a policy, which prescribes, for each state, an action to perform. Formally, a policy π is a function from states to actions: $\mathcal{S} \rightarrow Pr\left(\mathcal{A}\big(\pi(s)\big)\right)$, where $\mathcal{A}\big(\pi(s)\big)$denotes the action to be performed in state s.

In Q-Learning, the agent's objective is to learn a policy that maximizes some measure of the total reward accumulated over time. In principle, any number of reward measures can be used, however, the most prevalent measure is one based on a discounted sum of the reward received over time. This sum is called the return and is defined for time *t* as

$$Return(t) = \sum_{k=0}^{\infty} \gamma^k r_{t+1+k}\ , \tag{3.3}$$

where the discount rate, $0 \leq \gamma \leq 1$, determines the relative weighting of immediate and delayed rewards, and r_{t+1+k} is the reward received at time $t + 1 + k$. Because the process may be stochastic, the agent's objective is to find a policy that maximizes the expected return [69], [73].

The value function

Almost all RL algorithms are based on estimating value functions - functions of states (or of state-action pairs) that estimate how good it is for the agent to be in a given state (or how good it is to perform a given action in a given state). The notion of "how good" here is defined in terms of future rewards that can be expected, or, to be precise, in terms of expected return. Of course the rewards the agent can expect to receive in the future depend on what actions it will take. Accordingly, value functions are defined with respect to particular policies [70].

For a fixed policy π, define $V^{\pi}(s)$, the value function for policy π, to be the expected return, given that the process begins in state s and follows policy π thereafter. The agent's objective is to find a policy, π^*, that is uniformly best for all possible states. That is, find π^*, such that

$$V^{\pi^*}(s) = max_{\pi} V^{\pi}(s) \;\; \forall \mathrm{s} \in \mathcal{S} \tag{3.4}$$

There is always at least one optimal policy, π^*, that achieves this maximum at all states $s \in \mathcal{S}$. The Principle of Optimality from dynamic programming [74] guarantees that for a discrete time, discrete Markov state there always exists a deterministic policy that is optimal. Furthermore, a policy π is optimal if and only if it satisfies the following relationship:

$$Q^{\pi}(s,\pi(s)) = \max_{\mathrm{a}\in\mathcal{A}} \left(Q^{\pi}(s,a)\right) \quad \forall \mathrm{s} \in \mathcal{S} \tag{3.5}$$

where $Q^{\pi}(s,a)$, the action-value function, is defined to be the expected return given that the agent starts in state s, applies action a once, and follows policy π thereafter. Intuitively, Eq. 3.5 states that a policy is optimal if and only if in each state, the policy specifies an action that maximizes the local "action-value". That is,

$$\pi^*(s) = \; a \; such \; that \; Q^{\pi^*}(s,a) = \; max_{b\in\mathcal{A}} \left(Q^{\pi^*}(s,b)\right) \quad \forall s \in \mathcal{S} \tag{3.6}$$

and

$$V^{\pi^*}(s) = max_{a\in\mathcal{A}}\left[Q^{\pi^*}(s,a)\right] \;\; \forall s \in \mathcal{S} \tag{3.7}$$

For a given MDP, the set of action-values for which Eq. 3.7 holds is unique. These values are said to define the optimal action-value function Q^* for the MDP [69].

The Q-learning algorithm

One-step Q-Learning of Watkins [68], or simply Q-Learning, is a simple incremental algorithm developed from the theory of dynamic programming for delayed reinforcement learning. In Q-Learning, policies and value function are represented by a two-dimensional lookup table indexed by state-action pairs. The Q-Learning algorithm works by maintaining an *estimate* of the Q^*, which is denoted by Q^{π^*}, and adjusting Q^{π^*}values (often just called *Q-values*) based on actions taken and reward received. This is done using Sutton's prediction difference, or temporal-difference

(TD[52]) error [75] – the difference between the immediate reward received plus the discounted value of the next state and the Q-value of the current state-action pair [76]:

$$TD\ target = r + \gamma V^{\pi^*}(s') - Q^{\pi^*}(s,a), \tag{3.8}$$

where r is the immediate reward, s' is the next state, resulting from taking action a in state s and, considering Eq. 3.8, $V^{\pi^*}(s) = max_{a \in \mathcal{A}}\, Q^{\pi^*}(s,a)$.

Formally, the Q-Learning algorithm can be described as follows. The Q-values are estimated on the basis of experience, starting from arbitrary initial values (e.g., uniformly zero). After initialization, the agent enters the main control/learning loop, which consists of three basic steps [77]:

1. From the current state s, select an action a, receiving an immediate reward r, and arrive at a next state s';

2. Based on this experience, update $Q(s,a)$ to $Q(s,a) + \Delta Q(s,a)$ using following updating rule:

   $$\Delta Q(s,a) = \alpha[r + \gamma\, max_b\, Q(s',b) - Q(s,a)], \tag{3.9}$$

   where α is the learning rate, $\alpha \in (0,1]$, and γ is the discount factor. Equivalently, letting $Q^N(s,a) = Q(s,a) + \Delta Q(s,a)$ denote the new Q-value, a suitable manipulation of (3.9) indicates that the new Q-value is formed as a weighted average of old and new estimates as follows:

   $$Q^N(s,a) = (1-\alpha)Q(s,a) + \alpha[r + \gamma\, max_b\, Q(s',b)]. \tag{3.10}$$

3. Return to step 1.

Once the Q-values have been learned, the optimal action from any state is the one with the highest Q-value. The general form of the update rule

$$Q^N(s,a) = Q(s,a) + \Delta Q(s,a) = Q(s,a) + \alpha[r + \gamma\, max_b\, Q(s',b) - Q(s,a)] \tag{3.11}$$

can be written as:

$$NewEstimate = OldEstimate + \gamma[Target - OldEstimate]. \tag{3.12}$$

As already mentioned, for the learning algorithm the difference $[Target - OldEstimate]$ represents some "error" in the estimate. The target is presumed to indicate the direction in which to move, although it may be noisy, and γ is the corresponding step size. If γ satisfies the following conditions:

$$\sum_{n=1}^{\infty} \gamma_n = \infty \qquad \text{and} \qquad \sum_{n=1}^{\infty} (\gamma_n)^2 < \infty, \tag{3.13}$$

[52] TD learning is a combination of Monte Carlo ideas and dynamic programming (DP) ideas. Like Monte Carlo methods, TD methods can learn directly from raw experience without a model of the environment's dynamics. Like DP, TD methods update estimates based in part on other learned estimates, without waiting for a final outcome (they bootstrap) [70]

convergence can be established [78]. The first condition is required to guarantee that the steps are large enough to eventually overcome any initialization or path dependent fluctuation of the estimated Q-values. The second condition guarantees that the update steps become small enough to allow for convergence. While a simple choice of $\gamma_n = {}^{1}/_{n}$ satisfies the conditions of Eq. 3.13, setting $\gamma_n = \gamma$ as constant does not meet these conditions. In the latter case, estimates never completely converge as the new realization always leads to the same scaled update the Q-value, independently of the number of updates already made on this particular state-action combination. However, this can be a desirable feature in a non-stationary environment with time-varying migration functions f_t, e.g. for tasks with online learning on real-time market data where stationarity cannot be presumed and no migration function is known (optimizing of the market performance of a TSO belongs to this type of tasks). On the other hand, step size parameters that meet the conditions of Eq. 3.13 often require considerable tuning to obtain a satisfactory convergence rate. For this reason they are more of theoretical interest than used in real applications or empirical research [70], [78].

The algorithm is guaranteed to converge to the correct Q-values with probability one under certain specified conditions. These conditions include [77]:

- no action is neglected forever;
- the learning rate is suitably decreased over time;
- the environment is stationary;
- the state transition probabilities are Markov in the sense that the probability of transiting from s to s' depends only on s, s', and the current action a, and not on previous history.

3.2.2 Kalman filter

Forecasts are rarely perfect; instead they show what is likely to happen “on average”. So it is a good practice to complement forecasts with measures of the forecast uncertainty. The most common measure of uncertainty is the variance. Such measures are particularly useful for decision making.

The Kalman filter (KF) is an iterative computational algorithm designed to calculate forecasts and forecast variances for time series models. It can be applied to any time series model which can be written in “state space” form. Almost all of the standard time series models in common use can be written in this form.

The KF is applied recursively through time to construct forecasts and forecast variances. Each step of the process allows the next observation to be forecast based on the previous observation and the forecast of the previous observation. That is, each consecutive forecast is found by updating the previous forecast. The update rules for each forecast are weighted averages of the previous observation and the previous forecast error. These update rules resemble those of an allied approach to forecasting called exponential smoothing. The intriguing feature of the KF is that the weights in the update rules are chosen to ensure that the forecast variances are minimised. These weights, referred to collectively as the Kalman gain, play a similar role to the so-called smoothing constants in exponential smoothing [93].

Figure 3-2 from [89] depicts the essential subjects forming the foundations for KF theory. Although it shows KF as the apex of a pyramid, it is itself is a part of the foundations of another discipline – modern control theory – and a proper subset of statistical decision theory.

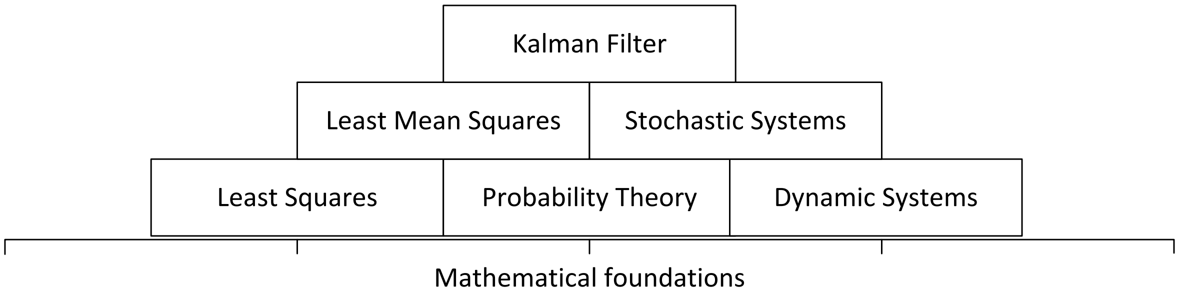

Figure 3-2: Foundational concepts in Kalman filtering

The fundamental concept of description of a dynamic system (linear or nonlinear) is according to Kalman [90] **the notion of the state**. By this is meant, intuitively, some quantitative information (a set of numbers, a function, etc.) which is the least amount of data one has to know about the past behaviour of the system in order to predict its future behaviour. The dynamics is then described in terms of state transitions, i.e., one must specify how one state is transformed into another as time passes.

The state of a dynamic system at a given instant of time is characterized by the instantaneous values of its attributes of interest. A state variable of a system is the associated real number. The state vector of a system has state variables as its component elements. This state vector is often denoted as x. The future state of a system may be determinable from its current state and future inputs. In order to do that, the dynamic behaviour of each state variable of the system must be a known function of the instantaneous values of other state variables and the system inputs [89]. The state-space model for a dynamic system represents these functional dependencies in terms of first-order differential equations (in continuous time) or difference equations (in discrete time). The differential or difference equations representing the behaviour of a dynamic system are called its state equations.

It is often of interest to determine the states occurring in points of time with fixed time intervals Δt: $t_k = t_0 + k\Delta t$ with $k \in \mathbb{N}$. For the sake of simplicity the notation of discrete time points t_k is shortened with an index k, correspondingly t_{k-1} with $k-1$ etc.

The KF addresses the general problem of trying to estimate the state $x \in \mathfrak{R}^n$ of a discrete-time process that is governed by the linear stochastic difference equation:

$$x_k = F_k x_{k-1} + B_k u_k + w_k, \tag{3.14}$$

where x_{k-1} is the n-dimensional system state vector at time t_{k-1}, x_k is its value at time $t_k > t_{k-1}$, F_k is the state transition matrix for the system at time t_k (relates the state at the previous time step $k-1$ to the state at the current step k). In addition to the actual system dynamic, expressed through the matrix F_k, the state equation also models other, external influences on the system. Thereby a distinction is made between deterministic, i.e. completely identifiable, influences and the ones of a random nature. The deterministic part is presented by the control vector u_{k-1} and its dynamic in form of B_{k-1} (control-input matrix). The matrix B relates the optional control input $u \in \mathfrak{R}$ to the state x. The random, not detectable components are enclosed within a noise term w_{k-1}. This random variable is called the process noise and assumed to be normally distributed with a zero mean, having the covariance Q_k [89], [91]:

$$w_k \sim \mathcal{N}(0, Q_k). \tag{3.15}$$

Due to the unpredictability of the noise term the state vector also contains a certain amount of "randomness" and is thus a stochastic value, a random variable. The set of all state vectors form a special stochastic process, a Markov chain or a Markov model of first order, i.e. the state at a time point k depends merely on the immediate temporal predecessor at $k-1$.

The process of observation (measurement) of true states x_k, x_{k-1}, … must contain the characteristics of an observer or measuring equipment. It involves the biases that can be modelled and the unpredictable measurement noise. The corresponding observation (or measurement) equation is as follows:

$$z_k = Hx_k + v_k, \tag{3.16}$$

where the matrix H (its dimension is case specific) relates the state to the measurement z_k and v_k is the measurement noise which is assumed to be zero mean Gaussian white noise with covariance R_k:

$$v_k \sim \mathcal{N}(0, R_k). \tag{3.17}$$

The noise vectors at each step $\{w_1, \ldots\, w_k, v_1 \ldots\, v_k\}$ are all assumed to be mutually independent from each other.

The conducted measurement results often in only single realization of normally distributed random variable z_k. Then the inverse problem occurs, in particular, using the series of measurements with the values $z_1, z_2, z_3, z_4 \ldots$ to infer about the corresponding states $x_1, x_2, x_3, x_4 \ldots$

It is a fairly generally accepted fact that primary macroscopic sources of random phenomena are independent Gaussian processes. In most cases, observed random phenomena are not describable by independent random variables. The statistical dependence (correlation) between random signals observed at different times is usually explained by the presence of a dynamic system between the primary random source and the observer. Thus a random function of time may be thought of as the output of a dynamic system excited by an independent Gaussian random process [90].

An important property of Gaussian random signals is that they remain Gaussian after passing through a linear system. Assuming independent Gaussian primary random sources, if the observed random signal is also Gaussian, we may assume that the dynamic system between the observer and the primary source is linear. This conclusion may be forced on us also because of lack of detailed knowledge of the statistical properties of the observed random signal: Given any random process with known first and second-order averages, we can find a Gaussian random process with the same properties. Thus Gaussian distributions and linear dynamics are natural, mutually plausible assumptions particularly when the statistical data are scant [90].

Due to the linearity of the model and the assumptions made for the noise terms w and v the states that must be determined also remain normally distributed for all times. As generally known, the normal distribution is fully described by its mean and covariance, and therefore the filter problem for the state estimation is limited to the estimation of these two determining factors. A possible exact solution of this inverse problem is the discrete KF. It is a set of equations that returns the estimations of the mean and covariance of the state

$$\hat{x}_k \sim \mathcal{N}(\bar{x}_k, P_k) \tag{3.18}$$

on the basis of the measurement sequence $z_k, z_{k-1}, z_{k-2} \dots, z_1$. Hereby $\bar{x}_k$ denotes the true state and P_k – its covariance, which are normally uknown.

The discrete Kalman filter algorithm

The task of KF can be stated as: Given a system such as the one described with Eq. 3.14, how can we filter z so as to estimate the variable x while minimizing the effects of w and v?

KF algorithm suggests using a so-called *a priori* estimate $\hat{x}_{k|k-1}$ to predict an estimate for the output, $\hat{z}_k$.

$$\hat{x}_{k|k-1} = F\hat{x}_{k-1} + Bu_{k-1} \tag{3.19}$$

The difference between this estimated output and the actual output is called the *residual*, or *innovation*.

$$Residual = z_k - \hat{z}_k = z_k - H\hat{x}_{k|k-1} \tag{3.20}$$

If the residual is small, it generally means a good estimate was made; if it is large the estimate is bad. This information can be used to refine the estimate of x_k; this new estimate is called then the a *posteriori* estimate, $\hat{x}_k$. If the residual is small, so is the correction to the estimate. As the residual grows, so does the correction. The pertinent equation is:

$$\hat{x}_k = \hat{x}_{k|k-1} + K_k(Residual) = \hat{x}_{k|k-1} + K_k\left(z_k - H\hat{x}_{k|k-1}\right) \tag{3.21}$$

where K_k is called is the *Kalman gain* and used to refine the estimate.

The equations 3.19 and 3.21 for KF can be divided into two groups: *time update* equations and *measurement update* equations. As already shown, the time update equations are responsible for projecting forward (in time) the current state and error covariance estimates to obtain the a priori estimates for the next time step. The measurement update equations are responsible for the feedback—i.e. for incorporating a new measurement into the a priori estimate to obtain an improved a posteriori estimate [91].

The time update equations can also be thought of as predictor equations, while the measurement update equations can be thought of as corrector equations. Indeed the final estimation algorithm resembles that of a predictor-corrector algorithm for solving numerical problems as shown below in Figure 3-3.

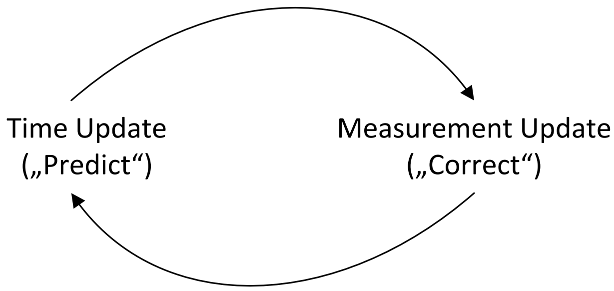

Figure 3-3: The ongoing discrete Kalman filter cycle

Since the goal is not only to define the actual variable x_k but also its covariance, the Eq. 3.19 receives an enhancement in the form of the appropriate estimation equation (Eq. 3.22). The control input u_k as well as its gain B are usually optional parameters, and since there are no influencing parameters in the current optimization problem (there is no control inputs that influence the curve of estimation variable), these are omitted in the following mathematical descriptions. Therefore the time update projects the current state estimate ahead in time as follows:

$$\hat{x}_{k|k-1} = F_k \hat{x}_{k-1} , \tag{3.22}$$

$$\hat{P}_{k|k-1} = F_k \hat{P}_{k-1} F_k^T + Q_k. \tag{3.23}$$

The index notation $k|k-1$ expresses the conditional nature of the estimates at the time points k and $k-1$ from each other. The superscript **T** denotes the transpose of the matrix marked accordingly.

The measurement update adjusts the projected estimate by an actual measurement at that time:

$$K_k = \hat{P}_{k|k-1} H^T \left(H \hat{P}_{k|k-1} H^T + R_k \right)^{-1}, \tag{3.24}$$

$$\hat{x}_k = \hat{x}_{k|k-1} + K_k \left(z_k - H \hat{x}_{k|k-1} \right), \tag{3.25}$$

$$\hat{P}_k = (\mathbb{I} - K_k H) \hat{P}_{k|k-1}. \tag{3.26}$$

The first task during the measurement update is to compute the Kalman gain, K_k. This matrix minimizes the a posteriori error covariance equation:

$$\hat{P}_k = \mathbb{E}\left[e_k, e_k^T \right], \tag{3.27}$$

where $$e_k = x_k - \hat{x}_k. \tag{3.28}$$

The next step is to actually measure the process to obtain z_k, and then to generate an a posteriori state estimate by incorporating the measurement as in Eq. 3.25. The final step is to obtain an a posteriori error covariance estimate via Eq. 3.26.

Looking at Eq. 3.25 it is evident that as the measurement error covariance approaches zero, the gain K weights the innovation more heavily. Specifically,

$$\lim_{R_k \to 0} K_k = H^{-1}$$

On the other hand, as the a priori estimate error covariance $\hat{P}_{k-1}$ ($\hat{P}_{k-1} = \mathbb{E}\left[e_{k-1}, e_{k-1}^T\right]$), approaches zero, the gain Kweights the innovation less heavily. Specifically,

$$\lim_{P_{k-1} \to 0} K_k = 0$$

Another way of thinking about the weighting by K is that as the measurement error covariance R approaches zero, the actual measurement z_k is “trusted” more and more, while the predicted measurement $H\hat{x}_{k|k-1}$ is trusted less and less. On the other hand, as the a priori estimate error covariance $\hat{P}_{k|k-1}$ approaches zero the actual measurement z_k is trusted less and less, while the predicted measurement $H\hat{x}_{k|k-1}$ is trusted more and more [91].

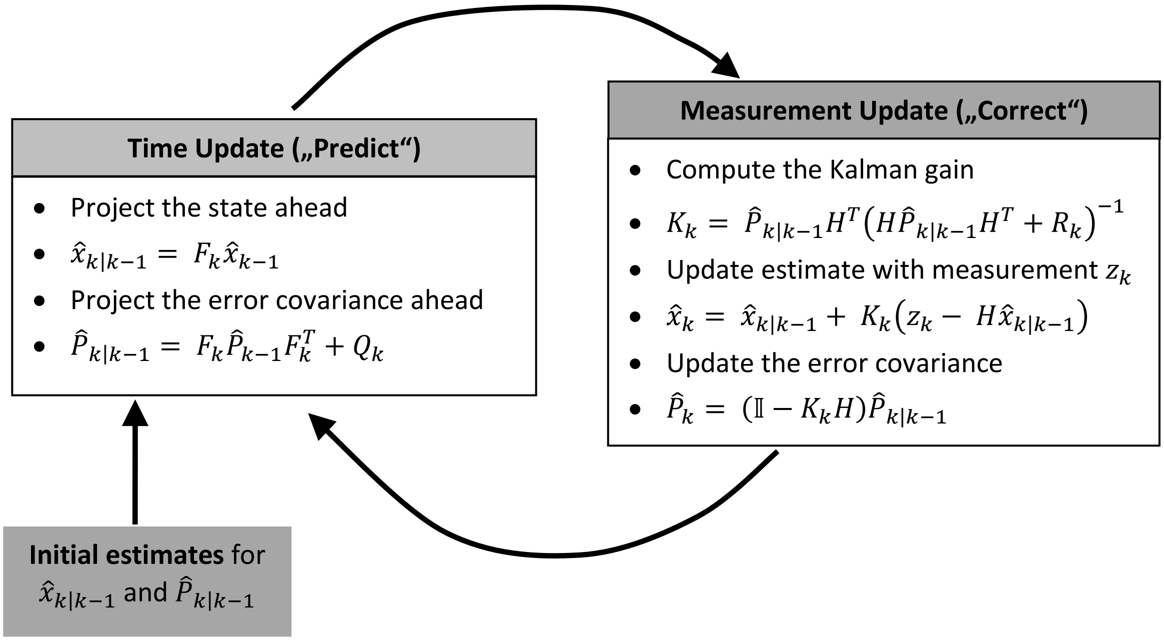

Figure 3-4: A complete picture of the operation of the Kalman filter

After each time and measurement update pair, the process is repeated with the previous a posteriori estimates used to project or predict the new a priori estimates. This recursive nature is one of the very appealing features of KF—it makes practical implementations much more feasible than (for example) an implementation of a Wiener filter [92] which is designed to operate on all of the data directly for each estimate. KF instead recursively conditions the current estimate on all of the past measurements [91]. Figure 3-4 above offers a complete picture of the operation of the filter, combining the high-level diagram of Figure 3-3 with the Eq. 3.24 … 3.28.

As can be seen from the correction equation (Measurement Update) the estimate of the mean depends on the observation linearly, KF is thus a linear filter. With increasing number of measurements the estimates for the mean and variance approach to their actual values arbitrarily exactly (that is what is called an unbiased and consistent estimator with minimum variance). Based on these estimation properties, which in this case correspond to the minimization of the mean squared error, the Kalman filter is an optimal[53] linear filter. Even generalized nonlinear filters do not yield better results for the linear state space model with normally distributed variables considered here. In contrast to other (recursive) linear estimators, which also minimize least squares, the Kalman filter also allows the treatment of problems with correlated noise components which are often observed in practice.

3.3 Application of the methods for the optimization task

Before starting with particular applications it is essential to explain, how the basic input information that is used for further optimization, is calculated within this thesis.

As previously emphasized not only day-ahead forecast of wind power feed-in in the respective control area is important for a TSO to participate on the power market, but the regulations of nationwide equalisation scheme, in particular that of HE. Actually only after this process is completed a TSO has the full information about the wind energy quantity it has to market on the EEX. Consequently it is crucial to model this process in order to know the exact amount of wind energy a TSO has on its control area. Unfortunately not all the information necessary for the modelling are provided for public access. Thus some modelling assumptions were made. They are presented in the next Subchapter.

3.3.1 Preliminary assumptions

In order to participate in the power market as a supplier of wind power each TSO must know (as exactly as possible) the quantity of wind power it has on it disposal. It means the wind power quantity in each of four control areas (RES BG) must be determined. To a certain extent this information a TSO receives from a WPF at 8 a.m. on the day-ahead of the actual power delivery. However, the quantities predicted by the WPF are only partly in ownership of an individual TSO, since a part of them must be exchanged within the process of HE.

To calculate which amounts of wind power are exchanged, the HE allocation key[54] is needed. This key shows in particular how much wind power from wind-rich regions (that of tps, 50Hertz) must be transported into the areas with less wind power generation but more power consumption needs (Amprion, EnBW).

The calculation of the HE allocation key is performed monthly, basing on the so-called “reference values”. They are calculated as follows:

$$Reference\ value_{i,m}[GWh] = FEC_{i,m}[GWh] - priv.FEC_{i,m}[GWh] + \text{"}deemed\text{"}\ special\ FEC_{i,m}[GWh]\ , \qquad (3.29)$$

[53] “optimal” means in this case unbiased and consistent with minimum variance
[54] The details of how are the amounts for HE are calculated are presented in Subchapter 2.2.3

where FEC is the final electricity consumption in each control area, $priv.FEC$ - privileged FEC[55], the index m stands for "month", i - for individual TSO and the "deemed" special FEC is determined as (see also Eq. 2.1):

$$"deemed"\ special\ FEC\ [GWh] = \frac{privileged\ RES{-}infeeds\ [GWh]}{RES{-}Quota\ [\%]} \tag{3.30}$$

However, all the relevant data: the monthly share of each TSO on the individual parameter (FEC (general and privileged), RES-feed-in (general and privileged) is not publicly available. Therefore some assumptions had to be made about these parameters based on the data that is publicly released. These were:

1) The share of the individual TSO on RES generation and final energy consumption in month (n/a[56]) does not change during a particular year (a[57]);

2) Through multiplication of monthly values of relevant parameters for Germany (a) with the shares, calculated in previous step, the monthly quantities for each individual area can be determined (n/a);

3) The monthly reference value of each parameter for individual TSOs is then calculated using Eq. 3.29 and Eq. 3.30.

After calculation of the HE allocation key, the quantities that are exchanged between the individual TSOs can be determined. Through the multiplication of the wind power quantity, a particular TSO has each hour (according to the WPF), with the HE allocation key of three other TSOs, a quantity to be transferred in each of these three control areas is calculated.

The difference between the quantities, a TSO gives and that, it takes, build the overall wind energy balance of its control area. If a TSO gives up more than it receives, this balance will be negative and vice versa. Thereby it is important to consider, that the nationwide sum of transferred and accepted quantities within the HE must be equal to zero (all the transferred wind power must be accepted). As a result, the wind energy available in each control area in every hour is determined.

The exemplary calculation of HE allocation key and exchanged wind power quantities for November 2008 is shown in Appendix A.

The same procedure is accomplished for the "real-time" values – the ex-post available measurements of wind power feed-in[58].

In order to understand the meaning of HE for a particular TSO, Figure 3-5 is presented. Two different variants of wind power availability are shown (exemplarily for 23.08.2007): on the left side – wind power feed-in in each of four control areas in the form they are generated by wind

[55] See Exceptional regulation in section 2.2.3
[56] Not available
[57] Available
[58] The information about wind energy feed-in (forecast and online projection ("real-time")) in four control areas was acquired from corresponding statistics, published by German TSOs on their Internet pages.

power plants existing in the control area of each TSO; on the right side – the availability of wind power after the exchange between TSOs. It is obvious, that the individual variability of wind power is smoothed through the HE. It means in particular, that each TSO has in principle the same wind stochastic that differs merely in volumes.

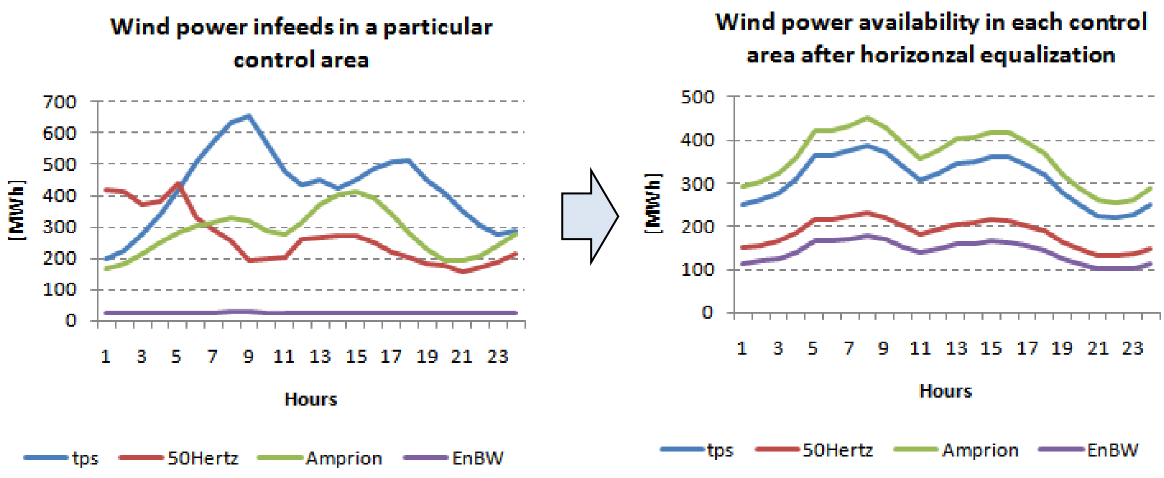

Figure 3-5: Wind power availability in each control area before and after horizontal equalisation

These moderated wind power feed-in are further compared with the delivery obligation of each TSO, which they have in accordance with the REA legislation that was in force till 01.01.2010 (EEG2004). It means in particular, that the determined wind power quantity in each control area is not the quantity that will be sold on the power market (as it is in the case of the EEG2009). The delivery commitment (RES-Quota[59]) to electric utilities previously existing in the RES balancing scheme must be deducted from this quantity. The result represents the bidding quantities for the day-ahead electricity market (called sublimation values (SVs) (Figure 3-6).

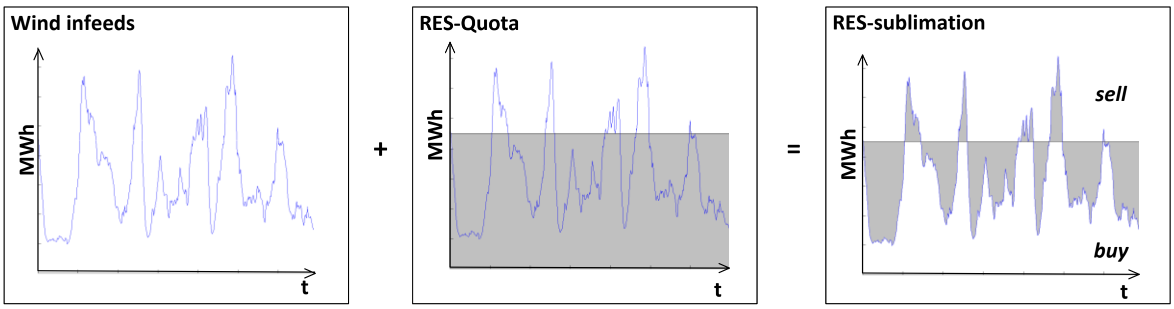

Figure 3-6: Calculation of the sublimation values

Thus **the input information** for further optimization steps includes **two time series**: day-ahead forecast and "real-time" values to sublimate in each control area in every hour.

These time series build the basis for further optimization with the help of the methods introduced before. With everything included is the optimization of a TSO'S market participation a certain kind of decision support tool for a particular operator (Figure 3-7).

[59] The monthly value of the RES-Quota determined by BDEW is thereby converted to its hourly equivalent.

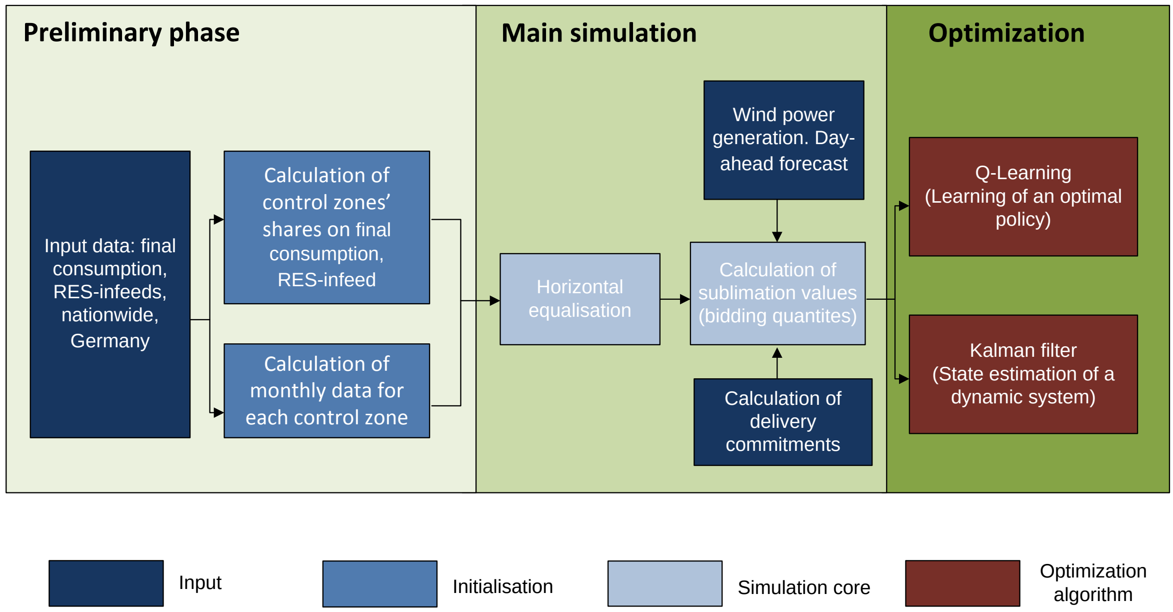

Figure 3-7: Decision support tool for a particular TSO operator

The next sections are dedicated to the description how the calculated SVs are involved into the respective optimization algorithm.

3.3.2 Q-Learning

In order to model the TSO's optimization problem in accordance with the Q-Learning principles it is first necessary to define the environment a TSO interact with.

Representations of states and actions as a part of the environment could have different layouts. So, in [67] 24 separate hourly market clearing price from the previous day are used for initializing of the 24 hourly states of the current trading day (numerical values); in [65] the states are indicated through the share of accepted supply quotes (percentage values). The actions can also be described through the numerical vectors, as in [66]; can have a character of an order (methods to change a supply rate, descriptive values), as in [65]; or can be presented in the form of movement command as in robotics. In our case numerical values are used for both state and action vectors.

As generally described, an environment is the tuple $(\mathcal{S},\mathcal{A},\mathcal{R})$, where $\mathcal{S}$ is the set of possible states, $\mathcal{A}$ is the set of possible actions, and $\mathcal{R}$ is the reward function. In the current model it is assumed, that a TSO as a learning agent interacts with its environment at each of a sequence of discrete time steps, $t = 0,1,2,\ldots$. Time steps symbolize the hours of each day of the year. Possible **states** within the current modelling framework are defined through the day-ahead forecast wind power available for trading in each control area in every hour (SVs), determined in accordance with the principles described in the previous section. It is the finite set, denoted as $S = \{s_1, s_2, s_3, \ldots, s_n\}$. The finite set of admissible **actions** an agent can take - $A = \{a_1, a_2, a_3, \ldots, a_n\}$, are the possible deviations to forecasted values, an agent consider to appear on the day of delivery. In the model, there are $n = 20$ states and actions.

While choosing the specific number of states and actions one must consider the update frequency of each state-action pair. While having all other parameters constant (in the current case the magnitude of SV's variation), the increasing of the number of the states leads to splitting of the Q-values. Since in this case the number of state-action pairs, which must be regularly updated, grows, their update must occur more often in order to keep them feasible. In view of the stable number of learning time steps, the increasing of the number of states results in sparse visiting of the state-action cells and thus to inadequate Q-values.

The dimensionality of the state space is validated by the magnitude of SV's variation. In the current model the largest range from all four TSO's was chosen for the design of the state space (that is from Amprion). Therefore in the cases of 50Hertz and EnBW, where the sublimation often do not reach the range limits, the Q-values update occurs in the "central" part of Q-table, while the values in the limit cells remain at their initialized values (zeros). Figure 3-8 shows an example of the Q-table for 50Hertz.

		Actions												
		1	**2**	**3**	**4**	**5**	**6**	**...**	**15**	**16**	**17**	**18**	**19**	**20**
States	**1**	0	0	0	0	0	0		0	0	0	0	0	0
	2	0	0	0	0	0	0		0	0	0	0	0	0
	...							**...**						
	5	0	0	0	0	0	0		0	0	0	0	0	0
	6	0	0	0	0	0	0		0	0	0	0	0	0
	7	45	58	63	166	244	395		172	154	68	56	29	20
	8	63	109	166	262	404	584		359	300	83	117	70	49
	9	97	188	329	481	551	767		251	348	252	97	171	45
	10	189	306	503	359	395	259		364	572	185	66	79	66
	11	132	97	168	482	394	744		138	498	95	329	52	84
	12	12	447	90	796	521	236		19	408	83	1	36	20
	13	176	6	622	0	84	801		78	0	69	287	83	3
	14	0	0	0	0	0	0		0	0	0	0	0	0
	...							**...**						
	18	0	0	0	0	0	0		0	0	0	0	0	0
	19	0	0	0	0	0	0		0	0	0	0	0	0
	20	0	0	0	0	0	0		0	0	0	0	0	0

Figure 3-8: Example of a Q-table with the Q-values, updated and not

These are intervals that are equally distributed between their minimum and maximum values, as it is shown in Figure 3-9.

The same range of state vector (from -3500 MWh to +3500MWh) for each hour was used for all four TSOs, because the experiments conducted have proven, that the algorithm brings more improvement in comparison with the initial day-ahead forecast at these conditions as conversely.

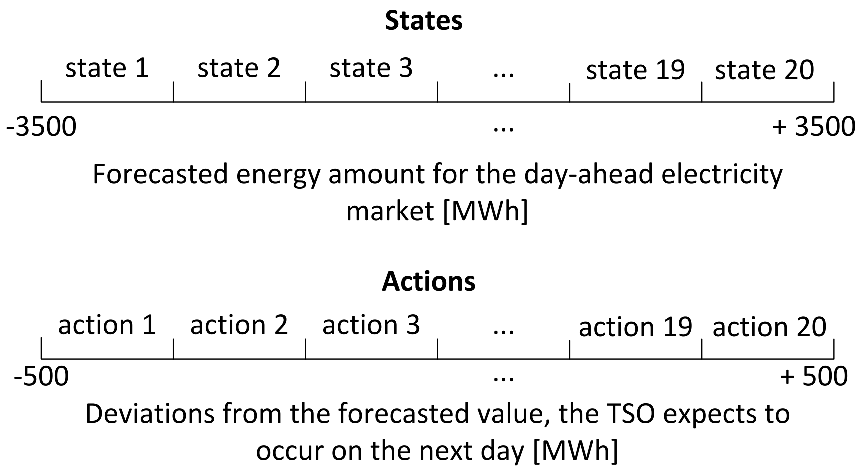

Figure 3-9: Q-Learning states and agent's actions

Dimensioning of the action space was performed in accordance with the distribution of the forecast error of the day-ahead prediction of SVs (Figure 3-10). The limits were set to [-500MWh, 500MWh] since the most deviations occur within this range.

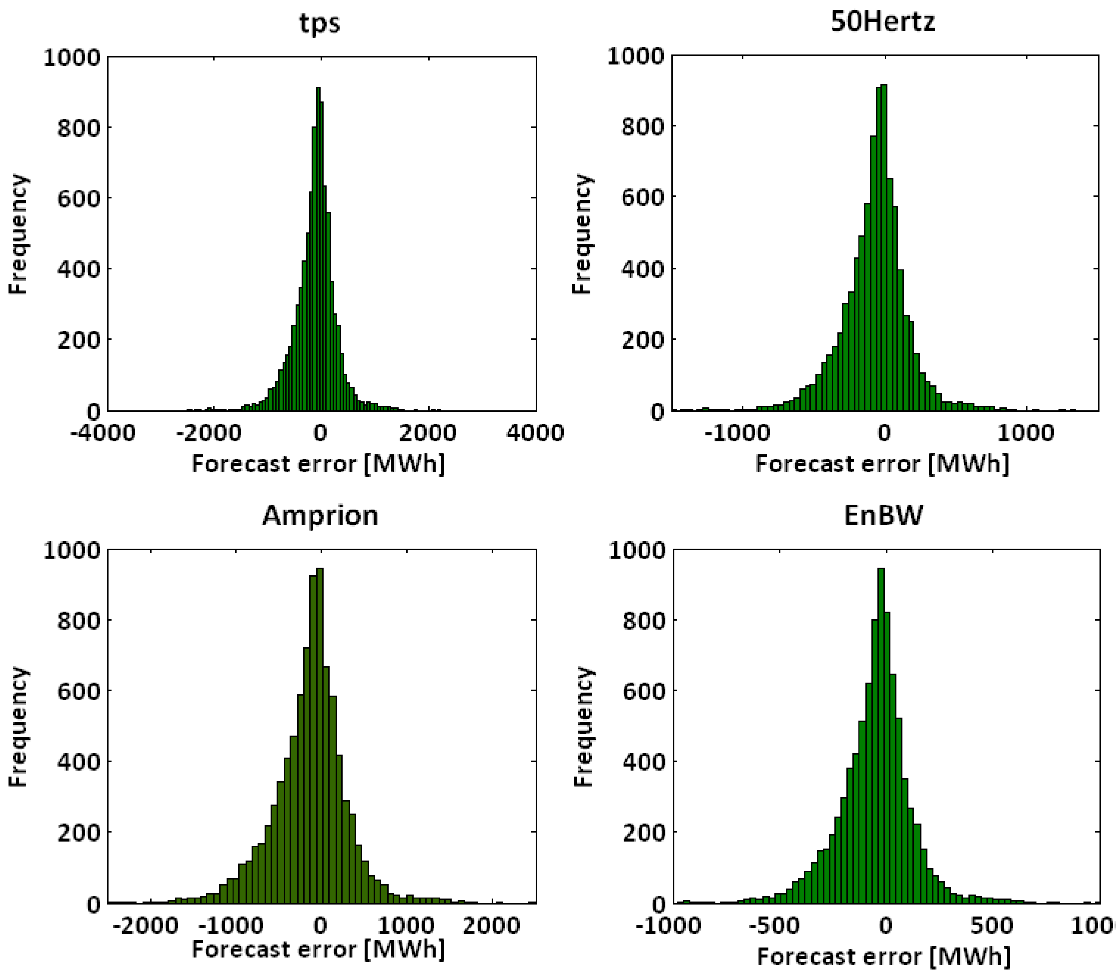

Figure 3-10: Frequency distribution of the forecast error (basis for the dimensionality of the action space)

As in the case with the increasing the number of states, the respective widening of the action space, leads to the splitting of the existent action intervals. However the deviations, which appear most frequently, are concentrated around the zero mark. It means that usually small quantities are necessary additionally for covering the difference between “real-time” SVs and their predictions. In this respect the increasing of the number of actions (while holding the dimensions constant) will lead neither to improvement nor to worsening of the achieved results, as long as the most frequent deviations remain considered.

As in the case with the state dimensioning, the same range of action vector was used for all four TSOs, because of the better performance.

Within this modelling framework a special MDP is considered, where the next state distribution is the same for each state, i.e. to [-3500MWh, 3500MWh]. It means that there is no influence between the action performed and the states reached, and the states are distributed i.d.d[60]. Moreover, the Q-learning occurs asynchronously, i.e. at each time step only one state-action pair is updated, not all the state-action pairs each time unit, as it were in the case of synchronous Q-learning.

The Q-Learning algorithm is implemented in two phases: during the first*, learning phase*, a TSO chooses its actions randomly in order to determine the initial arbitrary Q-values. This phase serves for the creation of the look-up Q-table. This table is used thereafter as a basis for optimal decision making. The Q-Learning algorithm works in the learning phase as follows:

1) At each time step, a TSO receives information about a certain level of sublimation value. It refers this quantity to the respective state.
2) After that it randomly chooses an action (the exploration strategy is used) – an additional quantity, it believes to be necessary to add/subtract to/from the current sublimation value in order to reach the “proper real-time” value.
3) The Q-Learning system compares the result of its action (sum of sublimation value and action) with the real-time data.
4) The **reward** is calculated in accordance with the integrated penalty function.

Penalty function was involved into the Q-Learning algorithm in order to emphasize the importance of prediction of the right deviation. If an agent chooses the “wrong” action, and the rest deviation after performing this action is large, the reward, it attains for its action, will be penalized, i.e. reduced. The extent, to which the reward is reduced, is defined through two variants of penalty function: linear and exponential (Figure 3-11).

They are calculated for each of the four TSO, as follows:

$$\pi_{i,t}(s,a)_{lin} = r_t - ratio \tag{3.31}$$

$$\pi_{i,t}(s,a)_{exp} = r_t * m * e^{-\frac{m*ratio}{r_t}} \tag{3.32}$$

[60] identically distributed data

where i is TSO's index, r_t is maximum profit a TSO can achieve for its action, $ratio$ is modulated difference between "real" SVs and forecasted SVs together with the chosen deviation (action), m is a parameter of exponential function and is set to 5.

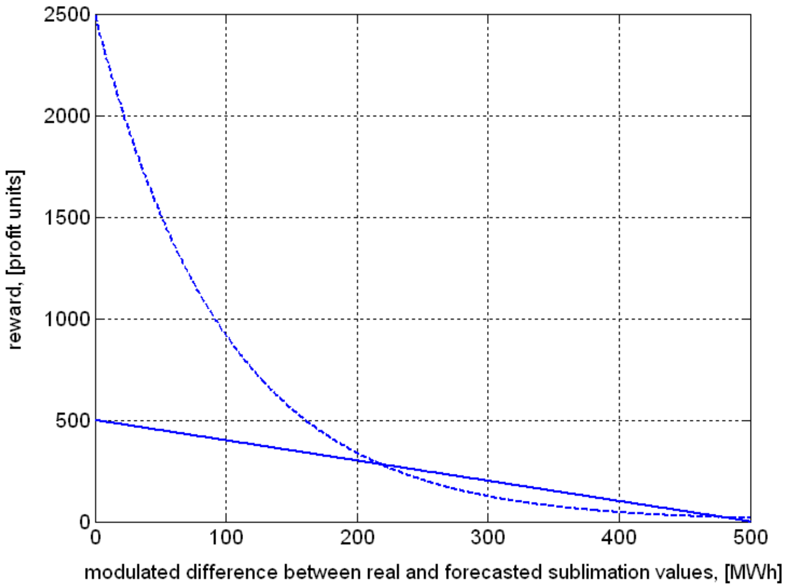

Figure 3-11: Penalty functions

The tests conducted have shown that the exponential penalty function usually results in better performance and since in an enhanced improvement of the day-ahead forecast of SVs that the linear penalty function.

In the current version of the Q-Learning implementation, no difference in penalty is envisaged for positive and negative deviations. Merely the degree of the deviation is decisive for the respective penalty, therefore $ratio$ has always a positive value. In further development of the algorithm this differentiation can be integrated, i.e. the positive deviations could be punished with greater decrease in reward, as the negative ones.

5) The Q-value is calculated in accordance with the Eq. 3.10. Thereby the learning factor α is calculated as follows:

$$\alpha_t(s,a) = \frac{1}{\beta_t(s,a)} \tag{3.33}$$

It means, that the learning rate α is designed to be state-action dependent varying with time. That is, the learning rate in the initial learning phase of simulation is inversely proportional to the visited number $\beta_t(s,a)$ of state-action pairs (s,a) up to the present trading day.

Learning rate is the degree to which estimated Q-values are altered by new data. High values imply more rapid updates, with a risk of instability; a factor of 0 will make the agent not learn anything. As states before in the learning phase this factor is inversely proportional to the visited number of state-action pairs. In the prediction phase it has a constant value of 0,5.

Authors of [80], referring to [81], prove the convergence of the Q-learning algorithm for the modelling case used in this thesis (asynchronous Q-learning, identical distribution of states, no influence between the performed action and the reached state). It was shown that, using the learning rate as in Eq. 3.33, the convergence rate has an exponential dependence on $1/(1-\gamma)$, where γ is the discount factor.

Further learning rates could be considered, e.g. a polynomial one ($1/t^{\omega}$), where $\omega \in (1/2,1)$). Using this learning rate leads to convergence of the Q-learning algorithm either, in this case the convergence rate will be polynomial in $1/(1-\gamma)$ [80]. For the test of the Q-Learning performance (reference case study) the discount factor γ is set to 0,1.

Each of Q-values, calculated in accordance with the Eq. 3.10, is then stored in the look-up Q-table in the respective state-action cell.

As a result a TSO receives a look-up Q-table, where all the Q-values are saved, which were learned during the learning phase. This table can be then used as a simple "if-then"-rule, as illustrated in Figure 3-12.

It means in particular, if a TSO receives a forecasted value that corresponds to one of the states, then it must add/subtract the additional value in order to correct the initial forecast.

if your forecasted value is within the limits [MWh]	[-1288:-921]	**then** the best action you can undertake is (the amount you should add to your market bid, [MWh])	-26,3
	[-920:-553]		-26,3
	[-552:-184]		-78,9
	[-184:184]		-184
	[185:552]		-26,3
	[553:920]		131,5
	[921:1288]		-236,8

Figure 3-12: Example of the "if-then"-rule deduced from the resultant Q-Table (here for 50Hertz, all values in MWh)

Moreover, the results from the learning phase can be used as a risk evaluation tool, since other values from Q-Table (apart from the maximum value) for the same state can be presented as a certain kind of likelihood function (Figure 3-13).

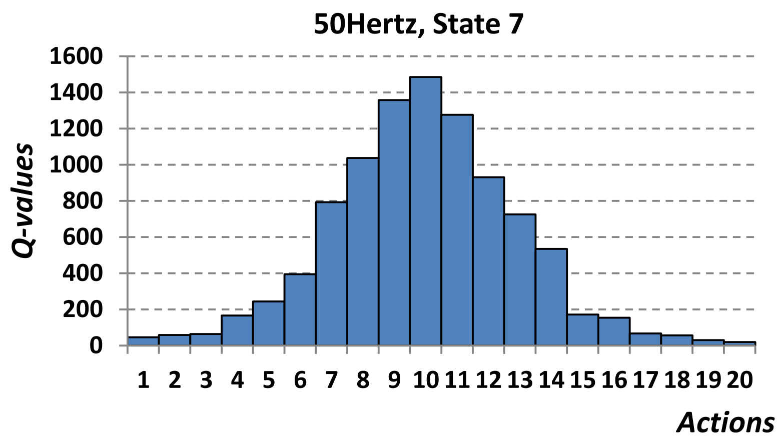

Figure 3-13: Exemplary optimization distribution for 50Hertz (state 7)

In accordance with this example, if a TSO operator receives a level of day-ahead forecast of SV that corresponds to the state 7 (SVs in the range [-1657:-1289] MWh), the best action he or she can perform in this situation is the action 10 (subtract from your market bid 26,3 MWh). The "next-best" action would be the action 9 (subtract from your market bid 78,9 MWh), further the 11 (add to your market bid 26,3 MWh), etc.

In the next step, the optimal policy calculated through the Q-Learning algorithm ("if-then"-rule) is tested in *the prediction phase*, where the produced Q-table is used for correction of the initial day-ahead forecast. As previously in the learning phase, at each time step, a TSO receives its sublimation value, it chooses the action with the highest Q-value (optimal policy) from the row of the Q-table that corresponds to the respective state (exploitation strategy). The reward is calculated in the same manner as in the learning phase. The system will continue to learn in the prediction phase, however with the fixed learning rate. The rate of 0,5 was chosen for ensuring the balance between rapid updates (high values of learning rate) and absence of learning (very small values). The discount factor remains unchanged.

The results of the prediction phase are then compared with the real-time data. The rest deviations, which remain after the optimization, means a forecast error. It is further used as the measure of evaluation of the Q-Learning performance.

Table 3-1 summarizes all the variables within the Q-Learning modelling and their counterparts from the TSO's real-world situation.

Table 3-1: Q-Learning application. Variables

Denotation	**Real-world counter-part**	**Internal parameter of the method**	**Description**	**Units**
States	x		day-ahead forecast of SV	MWh
Actions	x		possible deviations of the day-ahead forecast from the "real-time" SVs, a TSO can add/subtract to its market bid	MWh
Reward		x	combined with the integrated penalty function ensures that the "right" prediction of the deviation is rewarded with the higher Q-value and vice versa	
Q-Value		x	multilayer value, if maximal for certain state-action pair, determines the optimal policy for a TSO to follow, based on actions taken and reward received	
Learning rate		x	degree to which estimated Q-Values are altered by new data. High values imply more rapid updates, with a risk of instability; is inversely proportional to the visited number of state-action pairs	

Table 3-1. Continuation				
Denotation	**Real-world counter-part**	**Internal parameter of the method**	**Description**	**Units**
Discount factor		x	discounts future awards (small values imply that expected future rewards count for less)	
Rest deviation	x		forecast error of the Q-Learning	MWh

3.3.3 Kalman filter

As described before one can consider the input information a TSO obtain each day (day-ahead forecast) as a dynamic system with the certain stochastic that can be described by means of the Kalman filter (KF).

The challenging task in filter design consists in a correct description of the underlying process by means of two model equations of the KF: state and measurement equation. The former describes the target state evolution in time, which requires more or less exact knowledge of target dynamics. The latter bridges the target state with the measurement process, which involves knowledge about the sensor characteristics.

Within the KF modelling framework the "real-time" values are assumed to be a path, describing a certain development of a dynamic system. With the help of the Kalman algorithm it is tried to estimate the position of the system in each given period of time. There is no possibility to observe this path directly. The only information one has on its disposal is the measurements of this path (corrupted by measurement noise).

Accordingly the "real-time" values of sublimation are regarded as the system variables x_k to be estimated. The day-ahead forecast of the sublimation is used to define the measurements of the dynamic system z_k. Time periods k are defined to [1:24] within a day.

For definition of the initial values for state equation (Eq. 3.14) the last known "real-time" value is taken. Consequently, the initial values for $x_{k|k-1}$ and $P_{k|k-1}$ are defined as follows:

$$x_{0|0} = \begin{bmatrix} x_{RT} \\ x_{RT+1} - x_{RT} \end{bmatrix}, \tag{3.34}$$

where the state vector is formed by the last known "real-time" value (x_{rt})[61] and the velocity of the system is defined through the alteration of sublimation value in the next hour $(x_{rt+1} - x_{rt})$;

and

$$P_{0|0} = \begin{bmatrix} 0.1 & 0 \\ 0 & 0.1 \end{bmatrix} \tag{3.35}$$

[61] Subscript „*RT*" stands for „real-time"

Since there is no possibility to influence the system progress, there is no control input u_k and the corresponding matrix B in the model is absent in the present simulation. Therefore the Eq. 3.14 is simplified to:

$$x_{k|k-1} = Fx_{k-1|k-1} + w_{k-1|k-1}, \tag{3.36}$$

where $w_{k-1|k-1}$ is the process noise, which is normally distributed in accordance with Eq. 3.15. It is specified according to a common kinematic model as a scalar-valued *zero-mean white sequence* [93].

$$\mathbb{E}[w_{k-1}w_k] = \sigma_w^2 \delta_{k-1,k} \tag{3.37}$$

and enters into the dynamic equation as follows

$$x_{k|k-1} = Fx_{k-1|k-1} + \Gamma w_{k-1|k-1}, \tag{3.38}$$

where the *noise gain* Γ is an n_x-dimensional vector.

If it is assumed, that $w_{k-1|k-1}$ is the constant acceleration of the state position during the certain sampling period of length T, then the increment in the velocity during this period is $w_{k-1|k-1}T$, while the effect of this acceleration on the state position is $w_{k-1|k-1}{T^2}/{2}$ [93]. These assumptions indicate a belonging of the process to the piecewise constant acceleration model [93], which is of the second order and defined in accordance with the Eq.3.38.

The transition matrix is

$$F = \begin{bmatrix} 1 & T \\ 0 & 1 \end{bmatrix}, \tag{3.39}$$

and the vector gain multiplying the scalar process noise is given, in view of the above discussion, by

$$\Gamma = \begin{bmatrix} \frac{1}{2}T^2 \\ T \end{bmatrix}. \tag{3.40}$$

In the current model the sampling period is equal to the observation period and amounts to 1 hour.

The covariance Q of the process noise is used for specification the non-linearities in the state model (defined by Eq. 3.38). The variance of the process noise σ_w^2 is given through the deviations of the process from its linear approximation (given the “start” position and the corresponding acceleration), as it is shown on Figure 3-14:

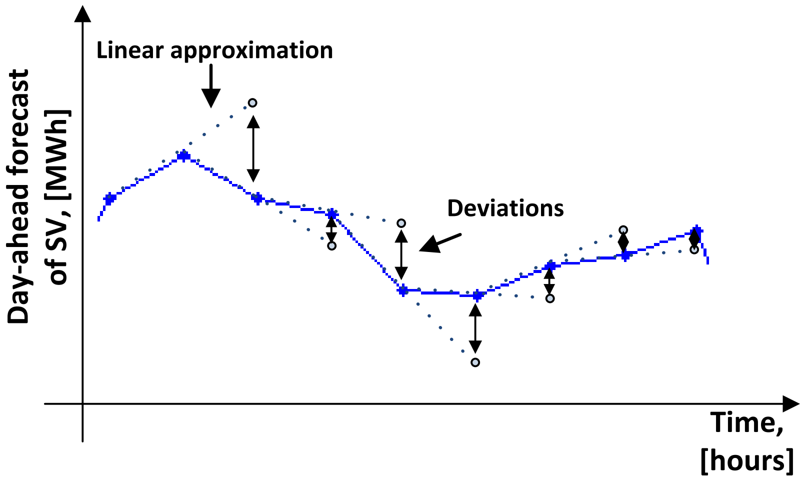

Figure 3-14: Process noise

Multiplied by the gain, Γ, the covariance Q of the process noise is

$$\begin{aligned} Q_k &= \mathbb{E}\left[\Gamma w_{k-1|k-1} w_{k-1|k-1} \Gamma^T\right] \\ &= \Gamma \sigma_w^2 \Gamma^T \\ &= \begin{bmatrix} \frac{1}{4}T^4 & \frac{1}{2}T^3 \\ \frac{1}{2}T^3 & T^2 \end{bmatrix} \sigma_w^2. \end{aligned} \tag{3.41}$$

It is further assumed, that the process of *observation* (measurement) of true states x_k, x_{k-1}, … is given by the day-ahead forecast of the SVs. These values z_k are related to the state vector by the means of linear observation equation:

$$z_k = \begin{bmatrix} 1 \\ 0 \end{bmatrix}^T \cdot x_k + v_k = H x_k + v_k. \tag{3.42}$$

The observation noise vector is characterized in accordance with Eq. 3.17. The corresponding observation noise matrix R_k is determined through the deviation of the day-ahead forecasted data in every hour k ($x_{DA,k}$) from the “real-time” process ($x_{RT,k}$):

$$R_k = \sigma_v^2 = \frac{1}{24} \sum_{\mathrm{k=1}}^{24} \left(\mathrm{x_{DA,k}} - \mathrm{x_{RT,k}}\right)^2 \tag{3.43}$$

In each simulation sequence the forecasted and “real-time” values from the last 24 hours are taken and the means and covariances of the Kalman filter calculated recursively in accordance with the algorithm from Figure 3-4. During the time update (prediction step) the state and state covariance estimates ($x_{k|k-1}$ and $P_{k|k-1}$) from the previous time step $k-1$ are propagated to the current time step k. As the current observation z_k becomes available the predicted state and covariance estimates are updated in the measurement update (correction step). Hereby the so called *innovation covariance matrix* S_k:

$$S_k = H \hat{P}_{k|k-1} H^T + R_k \tag{3.44}$$

and Kalman gain K_k are calculated. The former is a covariance matrix of the innovations or measurement residuals $z_k - H\hat{x}_{k|k-1}$, which are effectively the difference between the current and the predicted observation. The latter weights the innovation vector thus essentially affecting the updated state estimate. The matrices Q_k and R_k are altered with each sequence and thus reflect the latest changes in the variability of states and observations. Table 3-2 summarizes all the variables within the Kalman filter modelling framework.

Table 3-2: The Kalman filter application. Variables

Denotation	Real-world counter-part	Internal parameter of the method	Description	Units
States of the system, x_k	x		"real-time" values of SVs to predict	MWh
Measurements (observations), z_k	x		day-ahead forecast of SVs	MWh
w_k		x	process noise, which is normally distributed	
F		x	transition matrix	
Γ		x	noise gain	
Q_k		x	covariance of the process noise, used for specification the non-linearities in the state model	
H		x	observation noise vector	
σ_w^2		x	variance of the process noise, given through the deviations of the process from its linear approximation	
R_k		x	observation noise matrix, determined through the deviation of the day-ahead forecasted data in every hour from the real-time process	
S_k		x	innovation covariance matrix, a covariance matrix of the effectively differences between the current and the predicted observation	
K_k		x	Kalman gain, weights the innovation vector thus essentially affecting the updated state estimate	

Chapter 4

Case studies, results and their evaluation

In this Chapter methods motivated and described before are applied to the optimization task in accordance with modelling assumptions presented in the previous Chapter. It is started with case studies for the Q-Learning method, followed by performance test for the Kalman filter. Finally, advantages of both techniques are gathered within the framework of combined approach.

In order to measure how good the investigated methods predict the “real-time” values results of each case study are evaluated with the help of error measures. These quality indicators build the basis for comparison of the performance of each optimization method and of the initial day-ahead forecast. Section 4.1 gives a general overview of error measures that are usually applied for evaluation of WPF’s quality.

4.1 General definition of error measures

WPFs are characterized by an inherent uncertainty. It means in particular that no available wind power prediction can ever be exact. Therefore, it is essential that wind power forecasts are properly evaluated, not only to assess the performance of the chosen approaches adequately, but also to obtain a deeper understanding of what characterizes the prediction uncertainty.

Evaluation of the quality of forecasting methods is conducted by comparing wind power predictions made at a certain time directly with the actual corresponding observations. Hence, the quality of a given forecasting method is assessed through analysis of the deviation between the prediction and the truth (or the actual). The actions of determining and quantifying the quality of forecasting methods in terms of their statistical performance imply that there will be an evaluation of a long series of predictions, so that enough data is analyzed [40].

There are two basic criteria for illustrating a predictor performance: the Mean Absolute Error (MAE) and the Root Mean Squared Error (RMSE). In statistics, the MAE is a quantity used to measure how close forecasts or predictions are to the measured values. It is given by

$$MAE(|f_i - y_i|) = \frac{1}{N}\sum_{i=1}^{N}|f_i - y_i| = \frac{1}{N}\sum_{i=1}^{N}|e_i| \tag{4.1}$$

As the name suggests, the MAE is an average of the absolute errors $e_i = f_i - y_i$, where f_i is the predicted value and y_i the measured ("real-time") value. N stays for the length of prediction interval (number of forecasted values).

RMSE is a quadratic scoring rule which measures the average magnitude of the error. RMSE is a good measure of how accurately the forecast predicts the real-time values, and is the most important criterion for fit if the main purpose of the model is prediction:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(f_i - y_i)^2} = \sqrt{MAE\ ((f_i - y_i)^2)} \tag{4.2}$$

An alternative to the use of the RMSE is to consider the Standard Deviation of Errors (SDE):

$$SDE = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(f_i - \bar{f})^2} \tag{4.3}$$

The SDE criterion is an estimate for the standard deviation of the error distribution. It shows how much variation there is from the "average" (mean, $\bar{f}$). A low standard deviation indicates that the data points tend to be very close to the mean, whereas high standard deviation indicates that the data is spread out over a large range of values.

The MAE and the RMSE can be used together to diagnose the variation in the errors of forecasts. The RMSE will always be larger or equal to the MAE; the greater difference between them, the greater is the variance in the individual errors in the sample. If the RMSE=MAE, then all the errors are of the same magnitude. Both the MAE and RMSE can range from 0 to ∞. They are negatively-oriented scores: lower values indicate better fit.

Statistically, the values of MAE are associated with the first moment of the prediction error, and hence this is measure which is directly related to the produced energy. The values of RMSE and STD are associated with the second order moment, and hence to the variance of the prediction error. For the latter measures large prediction errors have the largest effect [40].

It might be of interest to highlight and to quantify the gain of preferring an advanced approach to the reference ones. This gain, denoted as an improvement with respect to the considered reference model (in this case the reference model is the initial day-ahead forecast, thus the subscript DA), is

$$Imp = \frac{EC_{DA} - EC}{EC_{DA}} * 100\%, \tag{4.4}$$

where EC is the considered Evaluation Criterion, which can be either MAE, RMSE, or even SDE – or the equivalent normalized versions. In following case studies MAE is considered as Evaluation Criterion.

4.2 Case studies. Q-Learning

Several case studies were conducted in order to discover the optimization ability of the Q-Learning method. First of all the general ability of the technique to outperform the day-ahead forecast of SVs was tested. Then the consequences of broadening of the learning periods are presented and thereupon the optimal length of learning/prediction intervals is examined. Finally the optimization of day-ahead market performance with the best frames for learning/prediction for one of four German TSOs is performed.

4.2.1 Performance test

The performance of the described Q-Learning was tested on the basis of wind feed-in data from the period of 2006-2007, provided online by TSOs [86]. The general improvement of the day-ahead forecast through implementing of the Q-Learning algorithm was tested in the reference case study [82]. Its performance was compared with the initial day-ahead forecast each TSO receives each day.

Experiments and results, described here, are based on the statistics of forecasted and real occurred wind energy feed-in from the year 2007[62]. The corresponding Q-Tables were learned during first 180 days of the year, the rest 154 days were used for testing (prediction phase). This combination of learning/prediction days was used to test the algorithm's prediction ability. It will be shown further (section 4.1.5) that the optimal configuration of learning/prediction days is crucial for the algorithm to perform properly.

Thereby the exponential function was used as a penalty function. Performance of the Q-Learning is presented in comparison with the initial day-ahead forecast available to TSO's operators. For the comparison presented in Figure 4-1 a measure to quantify the quality of prediction called **mean average (prediction) error** (MAE) is used (see Eq. 4.1).

Obviously the Q-Learning method provides the better results. In order to quantify the gain of the approach compared with the initial forecast one further measure is used called **Improvement** (see Eq. 4.4). Figure 4-2 shows the percentage ratio of superiority (improvement) of results of the Q-Learning in comparison with the initial day-ahead forecast based on MAE from the previous Figure.

[62] January 2007 is excluded from the consideration due to partly missing data

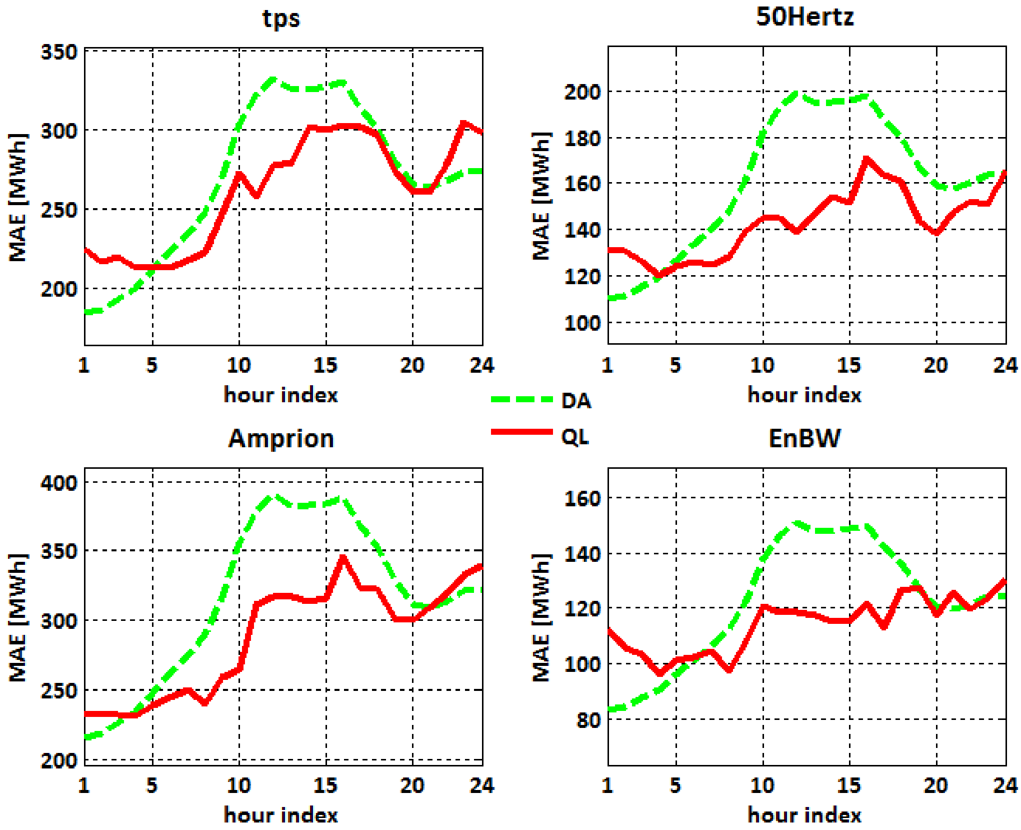

Figure 4-1: Comparison of the performance of Q-Learning (red, solid) and Day-Ahead forecast (dashed, green)

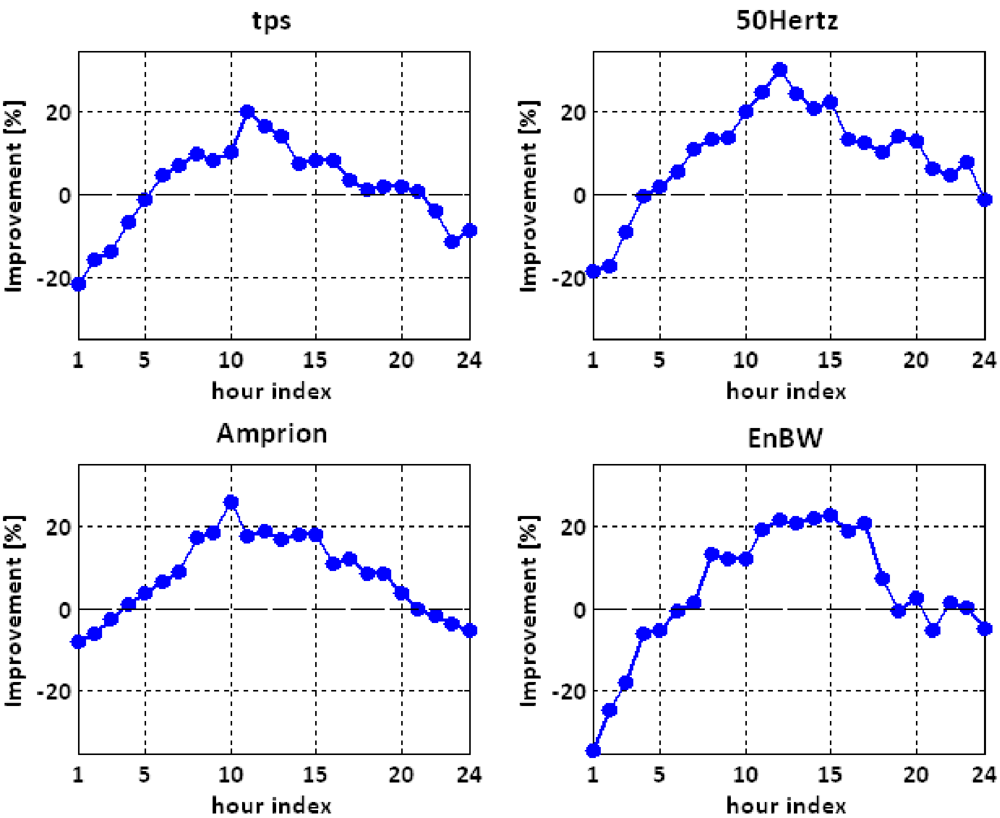

Figure 4-2: Improvement received through implementing of Q-Learning

It is seen, that in some cases implementation of the Q-Learning reduces the quantities that have to be balanced out in one hour on the next day on 30,3% (maximal value for 50Hertz in hour 12).

However, the quality of Q-Learning results in relation to early hours is less convincing. It is justified by the fact, that the deviations in these hours show high-amplitude dynamic of variation and since the limited number of learning data can barely be well learned. The way to improve this factor can be increasing the number of learning days and in this way the number of visiting of corresponding state-action pairs.

The better results of Q-Learning for 50Hertz and EnBW are explained by smaller volumes of wind energy feed-in they have to trade with (since their final energy consumption is less compared with other two TSOs). Since dynamic of their forecasted SVs nearly never achieves states [1…5] and [17…20], the Q-values corresponding to remaining states can be updated oftener and therefore lead to enhanced outcomes. In order to improve the performance of Q-Learning by other TSOs more learning data must be acquired.

4.2.2 Influence of internal model parameter

Penalty function

Additionally the influence of the art of penalty function on the achieved results was investigated. Comparison of exploring of different penalty functions by Q-Learning (linear and exponential) is presented on Figure 4-3.

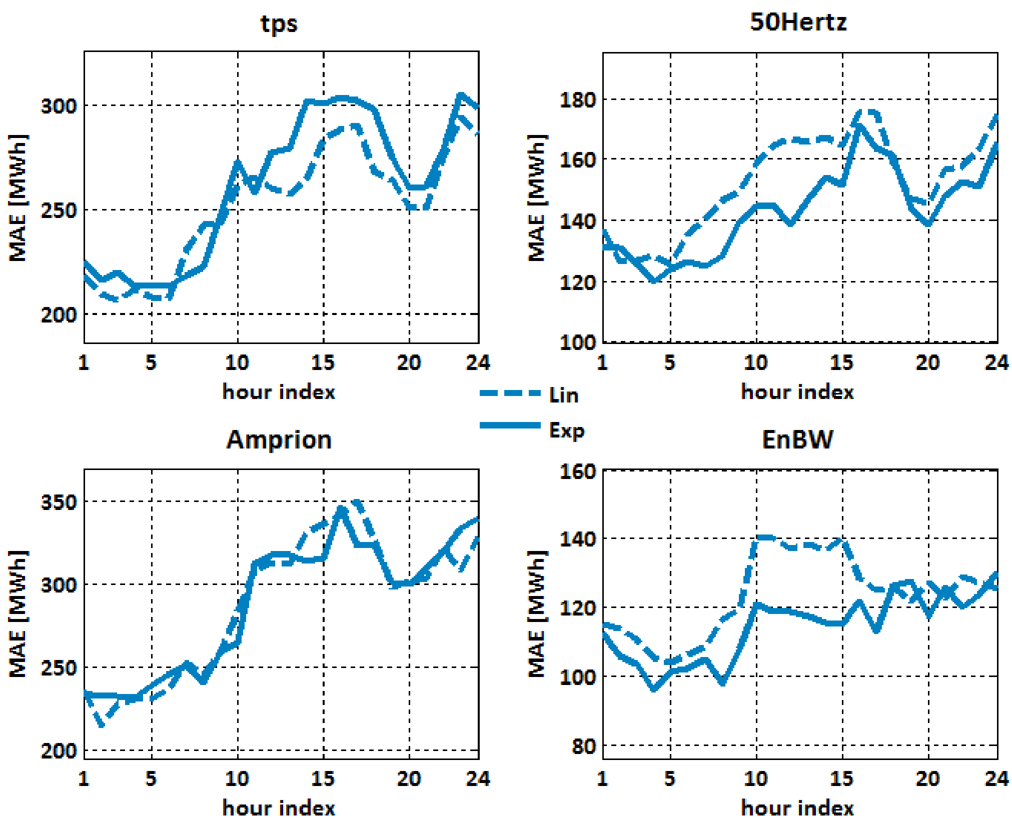

Figure 4-3: Comparison of using different penalty functions by the Q-Learning

It is clearly visible that despite of the fact that exponential penalty function brings better results for 50Hertz and EnBW, its exploring by Amprion yields almost no improvement, and by tps it is even better to apply linear function to obtain enhanced outcomes.

The results mean that if the Q-Learning will be implemented by individual TSOs a detailed case-related analysis of suitable learning parameter must be conducted.

Discount factor

The discount factor modifies future awards and determines their importance. It is in range $[0 \ldots 1]$. Small values imply that expected future rewards count for less. A factor of 0 will make the agent "opportunistic" by only considering current rewards, while a factor approaching 1 will make it strive for a long-term high reward. If the discount factor meets or exceeds 1, the Q-values will diverge.

When the discount factor is enabled (<1), it makes the reward reduce by time and hence the total reward at time t is given by:

$$R_t = r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \cdots + \gamma^n r_{t+n} + \ \ldots \tag{4.5}$$

In the tests conducted the variation of the discount factor led to following results. It was proven, that the increasing of the discounting from the initial value of 0,1 to its maximal value 0,9 (the value of 1 was not considered in order to avoid divergence) results in different quality of the Q-learning performance dependent on the particular hours (Figure 4-4, case for 50Hertz). Correspondingly, using high discount factor leads to superior results in the hours 9-12 (right side) comparing with the smaller one. In the same time, implementing the factor at the value of 0,1 surpasses the higher values in the hours 2-7 (left side).

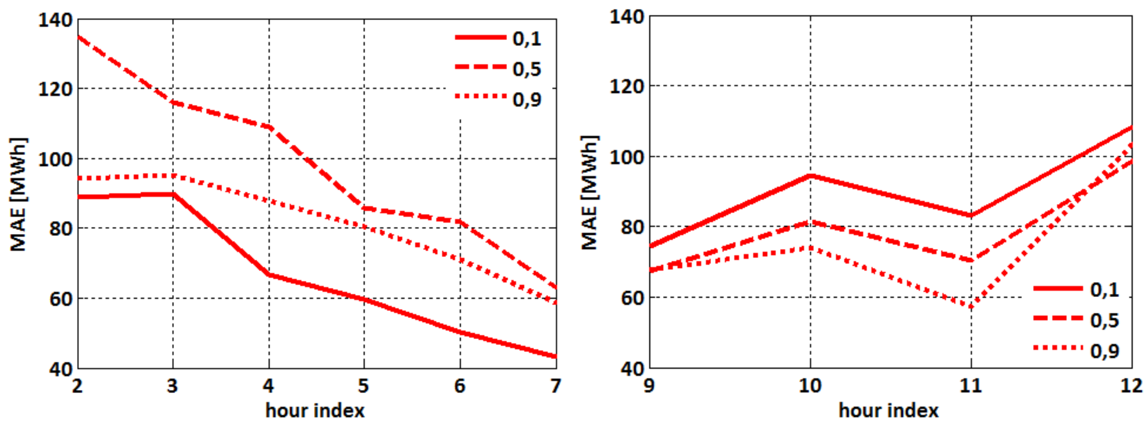

Figure 4-4: Influence of the discount factor on performance of the Q-Learning

4.2.3 Adding of further learning data

In the reference case study the implementation of the Q-Learning brought the best results for prediction of possible deviations in comparison the day-ahead forecast of TSOs. However, the performance of the Q-Learning was unsatisfactory e.g. at forecasting in early hours. To overcome this instability an assumption was made, that this problem could be eliminated through the adding of more learning data. The assumption was tested within the next case study, described here. To the real-world data about forecasted and "real" occurred wind energy feed-in from the year 2007 appropriate values were added from the year 2006.

However the results achieved showed that the performance of Q-Learning algorithm became worse. For comparison, on Figure 4-5, the results from the reference case study are shown with following parameters: 180 days for initial learning, and 154 days for prediction learning (2007) and the outcomes from recent experiments with parameters: 360 days for initial learning phase and 366 days of prediction (2006-2007). All other factors remained constant.

Degradation of results can be explained by several reasons. Firstly, the simple adding of data does not bring any improvement, but more stochastic and, therefore, more unstable data to consider. Secondly, different weather conditions in these two years provide different forecast values. It means in particular, that the data that was learned during the year 2006 may not be valid anymore for the year 2007.

Finally, the reasons for this difference can simply lie in the quantity of the averaged data. In the case of the year 2007, there were 154 days for averaging; in 2006 this amount was 366 days. Thus the increased number of data could have led to the increased mean error by averaging.

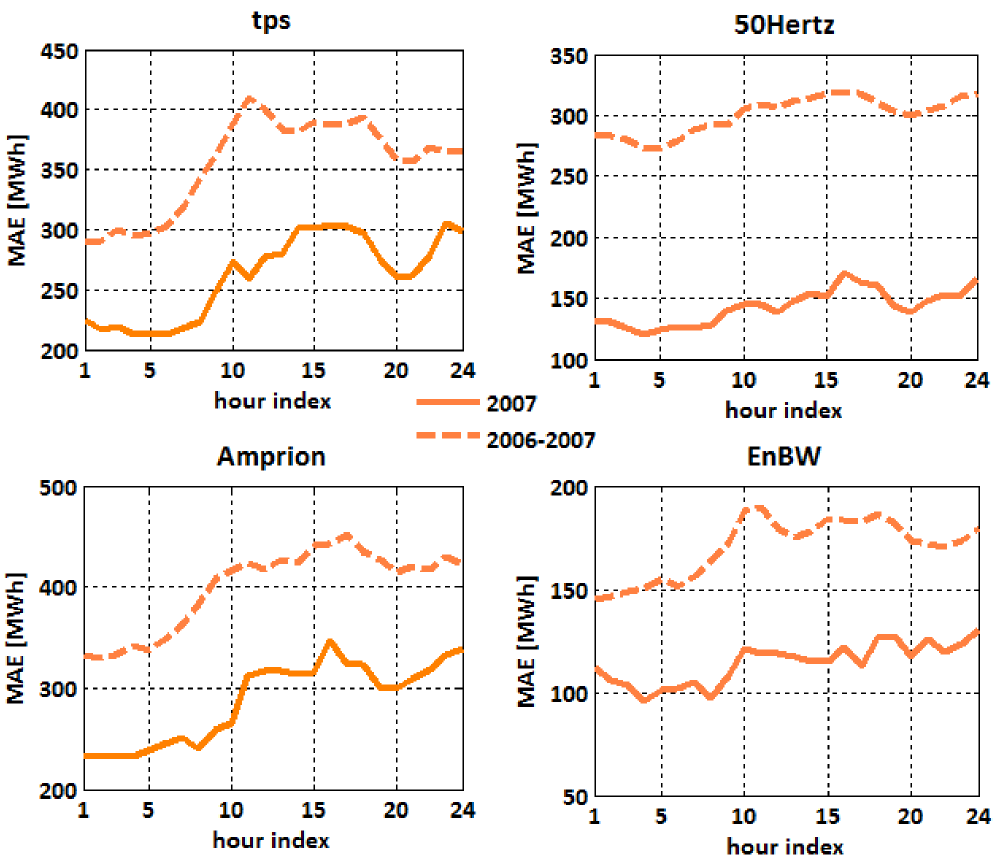

Figure 4-5: Results of including of additional learning data

Several conclusions can be drawn from these results for further simulations with Q-Learning algorithm:

1) It is not really an issue, how much data is provided for simulation. Certainly there must be enough to achieve feasible results. But once the sophisticated number of data is achieved, further increasing of this number may not contribute to improvement of simulation results. The exact quantity of learning days must be defined by tests since different input data may need different learning periods.

2) Wind generation data shows such stochastic characteristics as non-standard distributions, instationarity, complex chronological persistence, intermittency and interdependence phenomena [84], [85]. That's why a method must be found, which could learn this unstable behaviour (dynamic) and consider this in further predictions.

3) For proper forecasting of deviations of sublimation quantities with the Q-Learning method some special time frames (number of learning and prediction days) must be found, for which it provides the best results.

4.2.4 Optimal learning/prediction intervals

Within [83] the special attention is dedicated to the first and third mentioned conclusion. It was tried to find certain time frames for which the Q-Learning algorithm yields its best outcomes. Different combinations of learning/prediction days for each of four TSO were simulated and compared on the criterion of a smallest mean deviation for one day (for all 24 hours). For determination of the best time frame for learning/prediction the input data from two years – 2006 and 2007 – was used. The comparison was based on the method of "sliding window". It means in particular, that given the certain combination of learning/prediction days, their sum was taken from the beginning of testing data to implement the Q-Learning algorithm. Then the "window" "slides" from the beginning of the testing data on the number of prediction days and the Q-Learning algorithm is repeated for the next sum of learning/prediction days. This is replicated till the end of the testing data.

The combinations were formed from 14 variants for learning phase (from 50 till 180 days with an increment step of 10) and 9 variants for prediction phase (from 10 till 90 days with an increment step of 10). Since the achieved results are rather similar for all four TSOs and differs almost only in a value of rest deviation, just one of four graphics is shown on Figure 4-6, the one of tps.

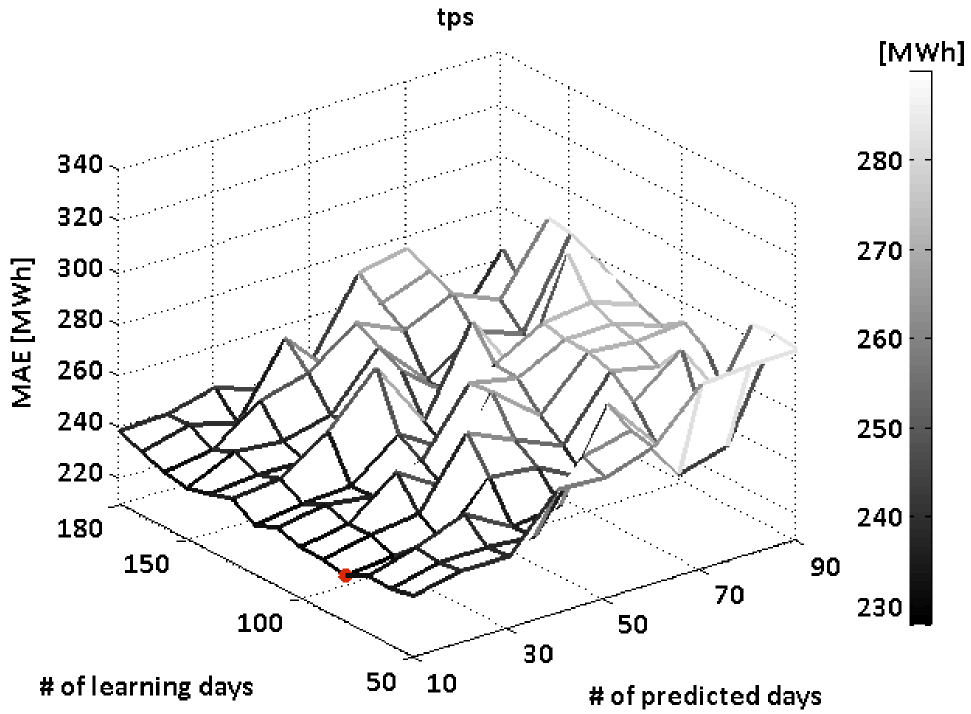

Figure 4-6: Comparison of different combinations of learning/prediction days for the Q-Learning algorithm

Through these simulations best combinations of learning/prediction days for each of four TSOs was found. These are as follows (Table 4-1):

Table 4-1: Best combinations of learning/prediction days for four TSOs

tps	50Hertz	Amprion	EnBW
80/10	110/10	90/10	140/10

It means in particular, that values of lookup Q-tables, gained by initial learning phase (which could last 80/110/90/140 days accordingly) can be used by TSO's operators during the next 10 days (predictions days) for correction of the day-ahead forecast. Afterwards another Q-values table must be generated. Number of learning days varies from TSO to TSO. It testifies to the fact, that wind feed-in data of each TSO has its individual stochastic characteristic. Consequently it takes from 80 till 140 days to learn these special features.

Using the best combination of learning/predictions days allows a TSO to improve the performance of its own Q-Learning algorithm. Figure 4-7 shows an example for 50Hertz (first 110/10 days were simulated, based on the data from 2006). On the left side the rest deviations after using ordinary day-ahead forecast (DA) and the Q-Learning algorithm (QL) are presented (10 days (240 hours) tested). On the right side the improvement of Q-Learning compared to day-ahead forecast is illustrated. Compared with results from Figure 4-1 and Figure 4-2 one can see that the performance of the Q-Learning in early hours could be significantly improved.

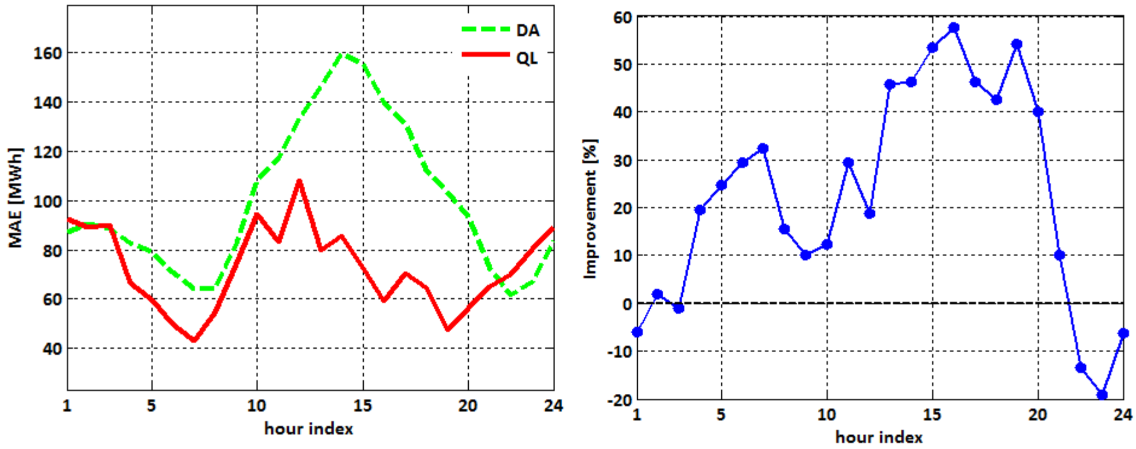

Figure 4-7: Comparison of using the best calculated combination of learning/prediction days with the initial day-ahead forecast

The achieved results indicate some conclusions about the performance of the Q-Learning algorithm:

- Q-Learning contributes a significant improvement to TSO's market performance (its forecast is about 10%-15% on average better than the performance of the initial day-ahead forecast);
- Improvement of even more percentage can be achieved if suitable learning/prediction time frames can be found (in individual cases improvement of 25%-30% on average can be achieved);
- However, performance of the Q-Learning in the early hours of a day is less convincing. As a rule, the ordinary day-ahead forecast predicts these hours better;
- This fact may be due to stochastic of the input data, which is not explicitly described with the algorithm;
- Further, for the application of the Q-Learning a certain waiting time for learning is necessary.

The last mentioned drawbacks of the Q-Learning were the reasons for search of an alternative method. This new approach should overcome the problems, listed above and still fulfill the requirements to the optimization method defined before. It means in particular, the alternative method must:

- Explicitly describe the system stochastic;
- Not need much time to get started;
- Outperform the prediction of the initial day-ahead forecast in the early hours of a day as far as possible.

In the next section the alternative approach that corresponds to these requests is presented.

4.3 Case studies. Kalman filter

With the initial modelling assumptions described in the section 3.3.3 the ability of the Kalman filter to surpass the initial day-ahead forecast of SVs was tested.

4.3.1 Performance test

The tests were conducted on the basis of wind feed-in data from the years 2006-2007[63] (726 days (17424 hours) tested). Time interval between each run of the KF is one hour. For the initialization of state vector $x_{0|0}$ the last two "real-time" values from the day $k-1$ are taken. The very last of these two is referred to as initial position, the difference between them – as velocity of the system. Based on this initialization and Eq. 3.35 the KF algorithm is started and the forecasts for the next 24 hours are made. Thereafter a new initialization is conducted in order to predict the system development for the next 24 hours. Results of the KF performance are presented on Figure 4-8.

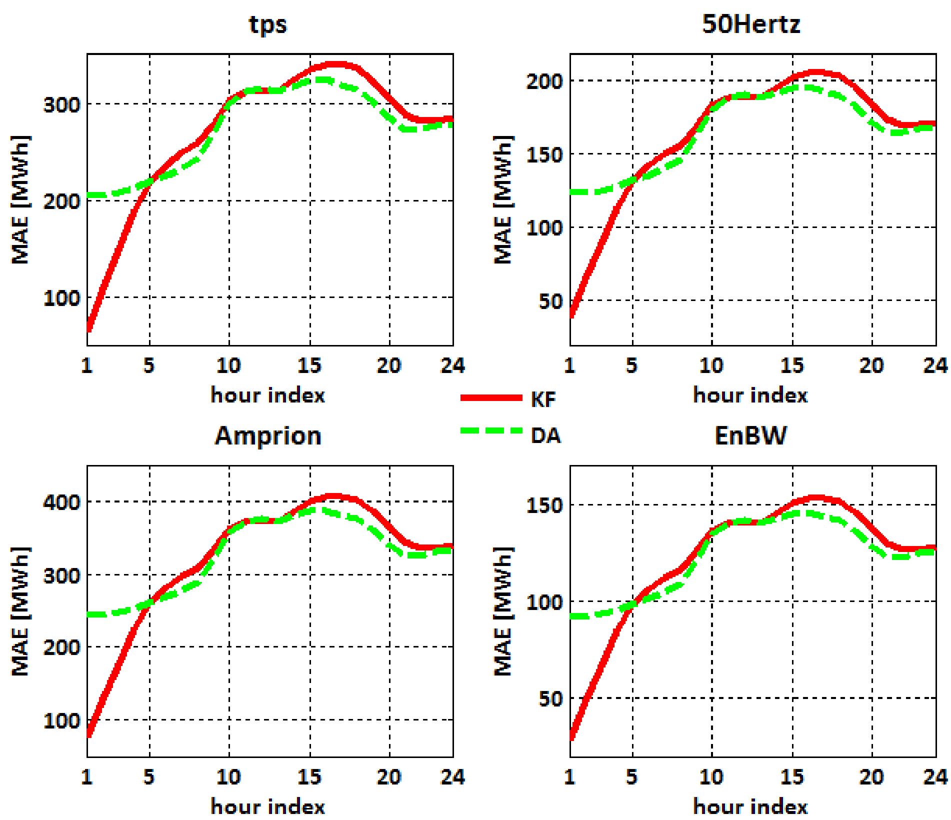

Figure 4-8: Comparison of the performance of the Kalman filter and Day-Ahead forecast

It is obvious, that the Kalman filter surpasses the initial day-ahead forecast significantly in the first five hours of the day. It is explained by the repeated application of "real-time" values at the initialization step. However, in the following hours the performance of the Kalman filter is notably influenced by day-ahead forecast, which is included into the simulation as the observation of the

[63] Some days with inaccurate values were excluded from the considerations

system behaviour. Although the Kalman filter achieves the improvement of almost 70% for the first hour of each day tested, it fails to follow the run of the real-time values curve because the system responses rapidly to the observation in the phase of state updating (large Kalman gain).

Figure 4-9 shows the percentage improvement of the forecast by means of the Kalman filter for all four TSOs (it is the same for all of them).

The mentioned "rapidness" of the system response can vary by alteration of observation error variance, R_k. If it is multiplied by a certain factor, it allows the system to revert to the forecasted values more slowly, and thus to predict the "real-time" values better. However, in the last day hours the inferior performance observed is strengthened and leads to major deviations to "real-time" values than before.

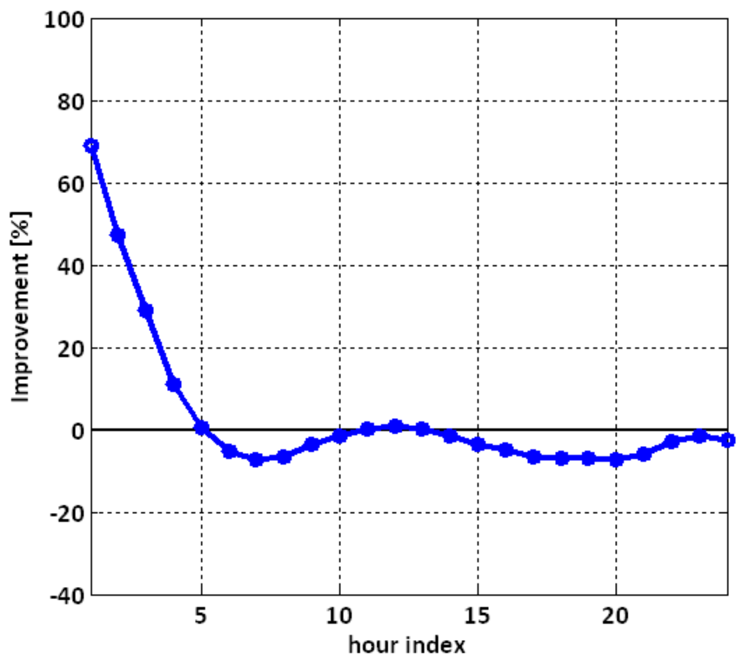

Figure 4-9: Improvement by Kalman filter in comparison with the initial day-ahead forecast (mean value based on 726 days tested)

The achieved results indicate some conclusions about the performance of the Kalman filter:

1) The Kalman filter predicts the wind power feed-in for first hours of each day (on average five) with very high accuracy (improvement up to 75% for one hour);

2) Improvement of even more percentage can be achieved for smaller number of days tested (i.e. for one day, improvement for the first hour up to 90%);

3) Strong dependence on the day-ahead forecast included in the modelling as the observations (z_k) of the system behaviour reduces the quality of prediction after first five hours;

4) This indicates that the day-ahead forecast does not correspond to the observation definition as it is to be found within the framework of the Kalman filter;

5) Prediction by means of the Kalman filter does not need any time for learning or similar. Only two "real-time" values from the previous day are necessary to optimize the trading decisions.

4.3.2 Changes in initial assumptions

In order to improve the performance of KF some changes were conducted in the phase of system modelling in comparison with performance test:

- The state error covariance matrix Q_k is calculated in accordance with equation (3.41). However, the variance σ_w^2 from this equation is initially set to the fixed value of 1000 and is not changed within the simulation; correspondingly Q_k must then be noted as Q, which means it is constant over time;

- The observation error covariance matrix R_k is set to the predetermined value of 10000. The same conditions as for Q_k are presumed for this factor: constant over time, therefore the notation is R;

- The state error covariance $P_{0|0}$ is set initially to

$$P_{0|0} = \begin{bmatrix} 100 & 0 \\ 0 & 10 \end{bmatrix} \tag{4.6}$$

  and is changed in each period of simulation;

- Just as in the performance test prediction by means of the KF is conducted on the basis from previous 24 hours for the next 24 hours of the next day;

- In this case the second step of the KF (correction) is absent due to absence of measurement data (day-ahead forecast is not regarded anymore).

In its first, prediction step, predicts the future states linearly, relying on the initial state position and velocity. In order to avoid the too high divergence in the prediction results, the estimated states are combined with the day-ahead forecast of sublimation values. It means in particular, that the certain amount of first hours, estimated by the prediction step of KF are taken as they are (because at the beginning these are very close to the real values), whereas the next estimates are weighted with a factor α ($\alpha < 1$), which is being declined as the sequence number of an hour increases. Therefore the last estimates of the KF (some hours till 24) are almost fully replaced by the day-ahead forecasted values, because they are more trustworthy than the state estimations of the KF. These weighting factors as well as the number of hours weighted can be allocated variously. The both parameters are those that can be modified to achieve the best result possible. One of the possible variants for weighting is shown on Figure 4-10. It is used in simulations, the results of which are presented further. This variant of weighting was chosen since it allows trusting the values of the KF in the early hours more (which are proved to be better than the initial forecast), and further the day-ahead forecast is used to correct the inaccuracy of the KF modelling results, until ultimately the values of the day-ahead forecast are fully undertaken for the late hours.

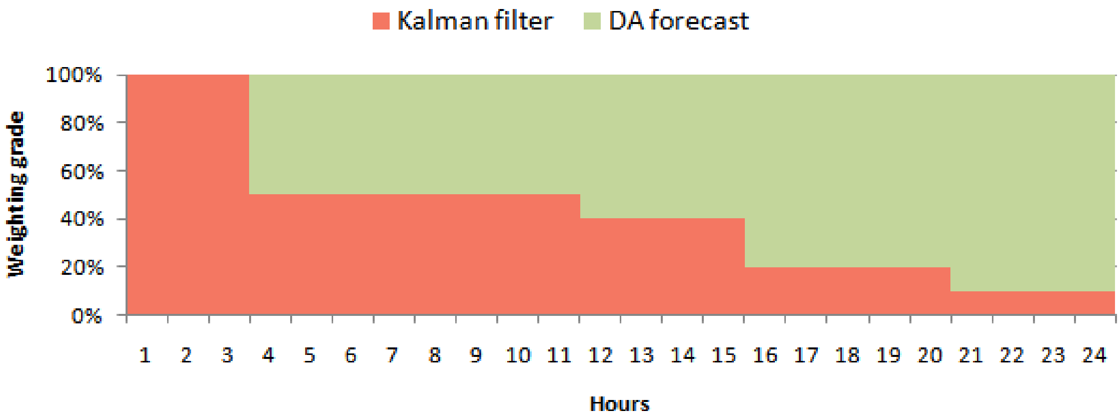

Figure 4-10: Weighting of the estimates made by the Kalman filter with the day-ahead forecast

According to Figure 4-10 the first six estimates provided by the KF are involved into the final prediction without any "correction"; the further hours are adjusted with the day-ahead forecast to receive more feasible results. Figure 4-11 also illustrates the reason for this weighting. For this simulation 10 days were taken for testing (case of 50Hertz).

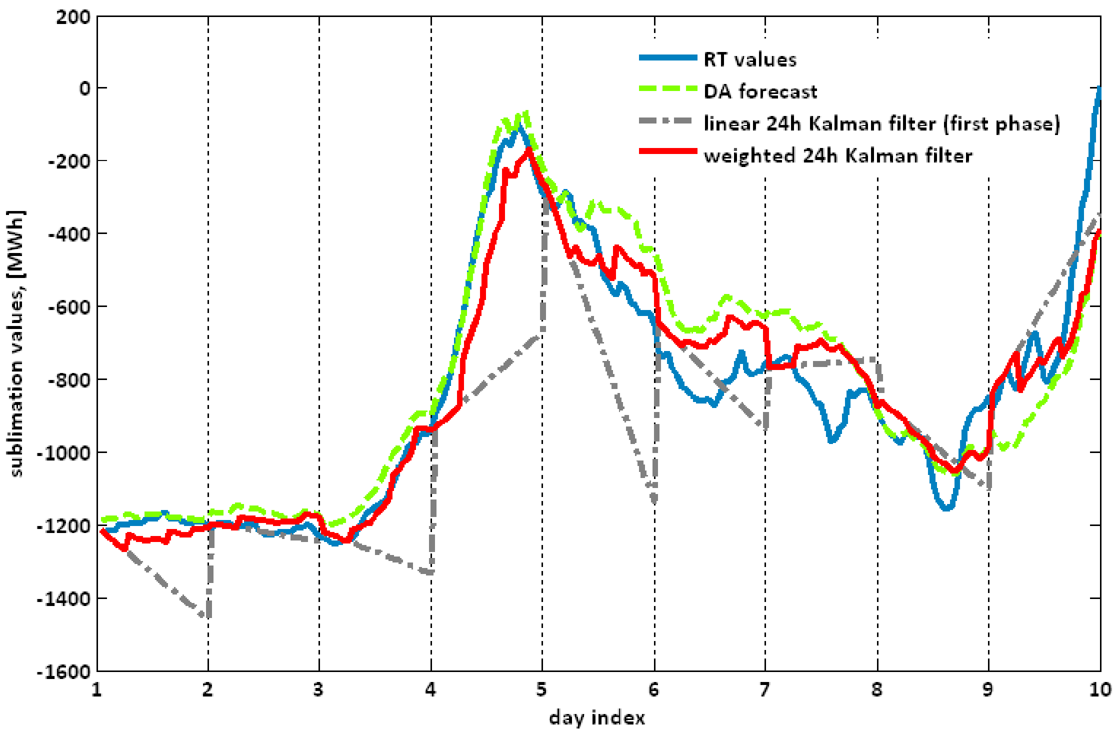

Figure 4-11: Simulation results. Prediction for 24 hours (testing period: 10 days)

Due to the linearity of the approach the state estimations of the Kalman filter launched by the initial state position and velocity swerve from the appropriate approximation and result in unfeasible predictions. Their weighting with the day-ahead forecast in turn allows avoiding this discrepancy. This compounding improves the day-ahead forecast itself on 20% (based on the cumulative prediction error for the shown case, Figure 4-12). Increasing the number of testing days leads to degradation of results.

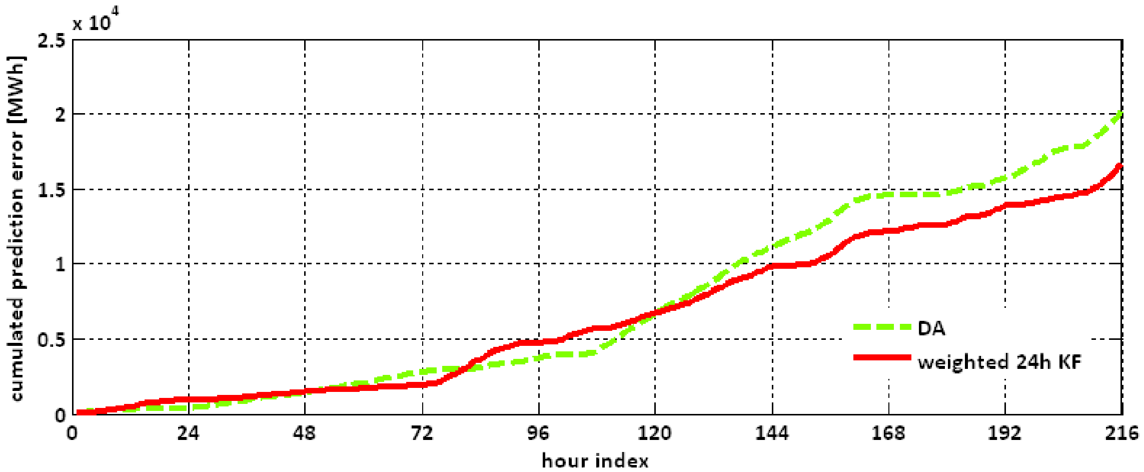

Figure 4-12: Cumulated prediction error. Comparison of day-ahead forecast and Kalman filter (testing period: 10 days)

4.3.3 Decreasing of the prediction interval

The performance of KF presented in the section 4.2.2 can be improved if the prediction horizon is reduced. It is assumed, that a TSO has the possibility to receive the actualized forecast with the real-time values for e.g. the past 6 hours and use it for prediction for the next 6 hours. The consideration of this updated information could improve the state estimations of the KF, as it is shown in Figure 4-13.

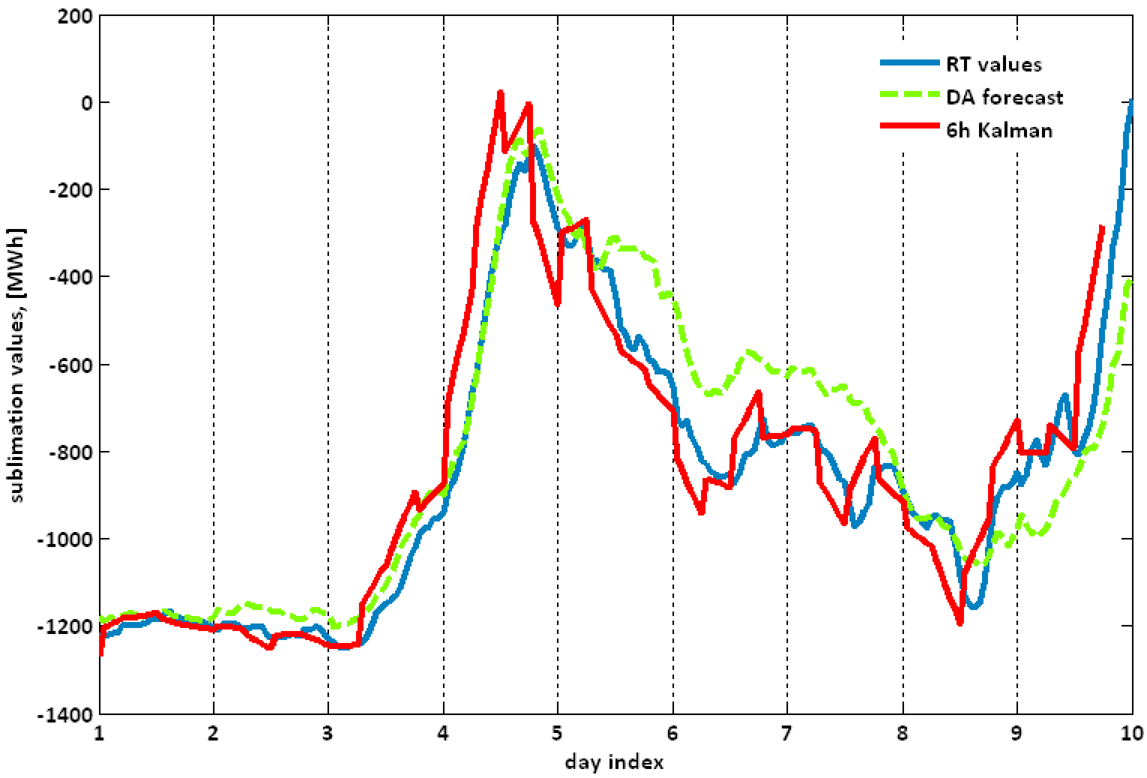

Figure 4-13: Simulation results. Prediction for 6 hours

In this case it is even not necessary to weight the estimates with the day-ahead forecast. The results shown improve the initial day-ahead forecast on 55% (for the given testing period, based on the cumulative prediction error, Figure 4-15 and Figure 4-15).

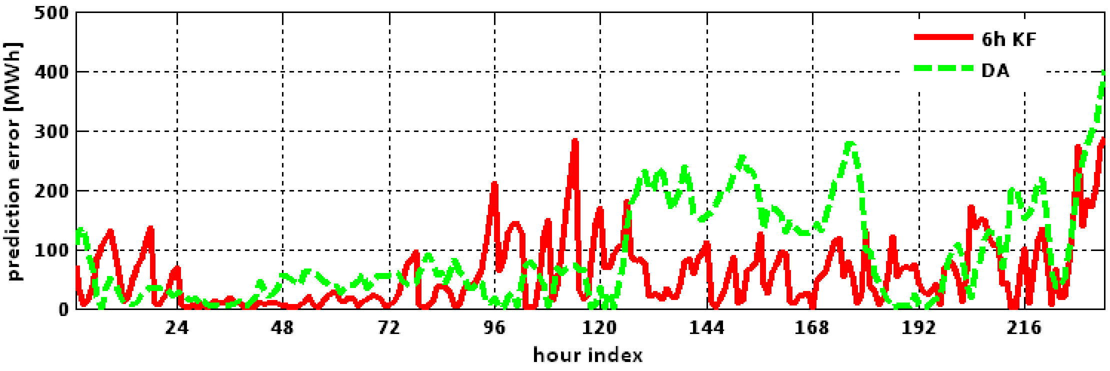

Figure 4-14: Prediction error with assumptions of section 4.2.2

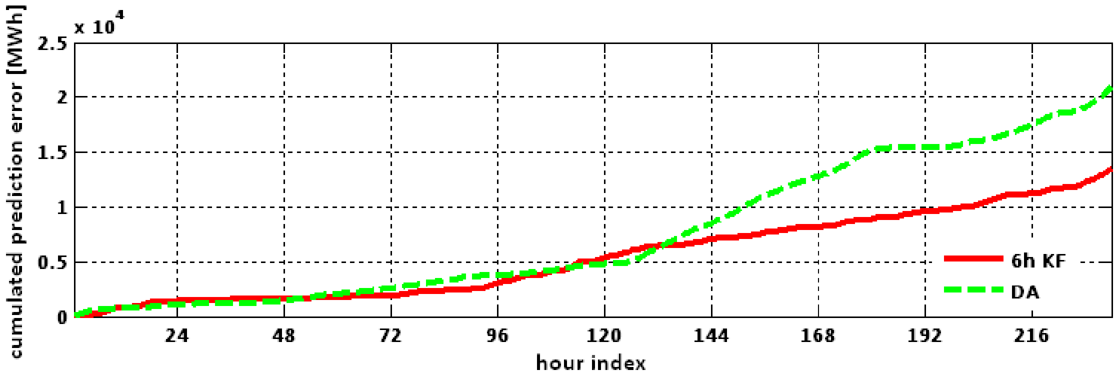

Figure 4-15: Cumulated sum of prediction error with assumptions of section 4.2.2

The results of performance test could also be significantly improved, if the prediction period is reduced (Figure 4-16).

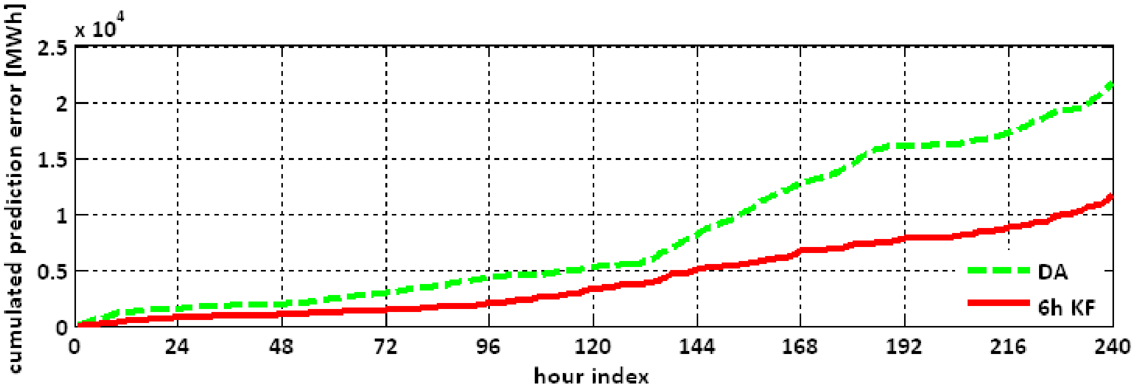

Figure 4-16: Cumulated sum of prediction error with assumptions of section 4.2.1

As shown in the previous section, weighting supports the stability of good performance of the Kalman filter as the testing period increases. For example, with the first three hours, predicted by means of KF, taken without any correction and the last three taken on the half (Figure 4-17), the weighted estimations outperform the uncorrected estimations with the increasing number of testing days as shown in Figure 4-18.

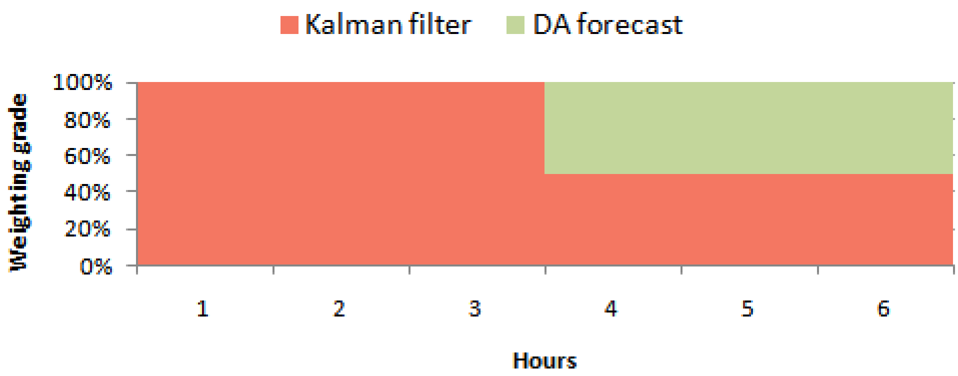

Figure 4-17: Weighting variant for the prediction of the next 6 hours

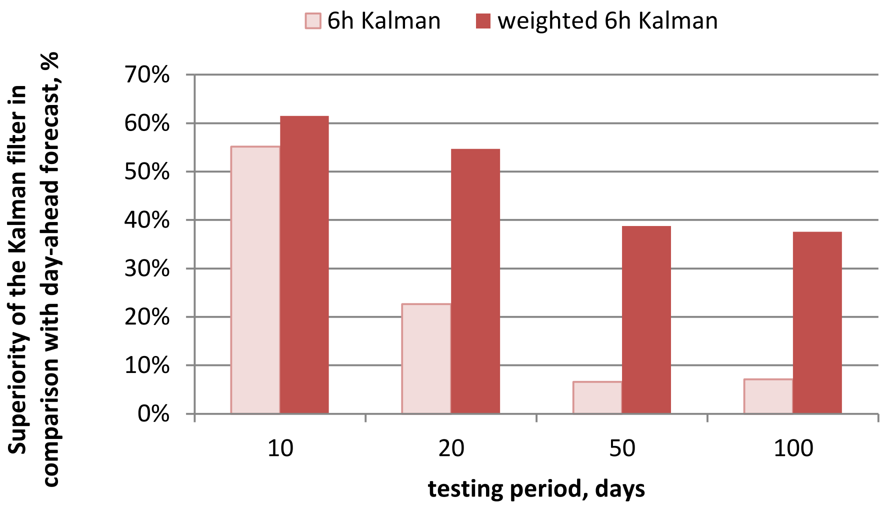

Figure 4-18: Comparison of weighted and unweighted estimations of the Kalman filter given the increasing number of testing days

For the further modelling with the help of the Kalman filter it is essential to consider following features.

It is important to remember that the Kalman gain and error covariance equations are independent of the actual observations. The covariance equations alone are that is required for characterizing the performance of a certain sensor system before it is actually built. At the beginning of the design phase of a measurement and estimation system, when neither real nor simulated data is available, just covariance calculations can be used to obtain preliminary indications of estimator performance [89].

In the actual implementation of the filter, the measurement noise covariance R is usually measured prior to operation of the filter. Measuring the measurement error covariance is generally practical (possible) because it is necessary to measure the process anyway (while operating the filter) so it should generally be possible to take some off-line sample measurements in order to determine the variance of the measurement noise.

The determination of the process noise covariance Q is generally more difficult as it is typically not possible to directly observe the process that is being estimated. Sometimes a relatively simple (poor) process model can produce acceptable results if one "injects" enough uncertainty into the process via the selection of Q. Certainly in this case one would hope that the process measurements are reliable.

In either case, whether or not a rational basis for choosing the parameters is available, often times superior filter performance (statistically speaking) can be obtained by tuning the filter parameters Q and R. The tuning is usually performed off-line, frequently with the help of another (distinct) Kalman filter in a process generally referred to as system identification [91].

4.4 Combined approach

In the recent time it is more and more often the tendency to be observed in wind power forecasting of combination of advantageous characteristics of individual forecasting models in one combined (or hybrid) approach [95]. In this way it is tried to merge the forecast accuracy of some models for the short-time horizons with the high levels of accuracy of another models for longer-term time horizons.

In the most of cases the physical and mathematical models are combined. Besides of beneficial fusion of forecasting abilities the physical model also allows the spatial resolution of the NWP forecasts to increase, taking the terrain characteristics into account, as well as forecasting without SCADA measures [41]. In the field of powerful forecasting tools that are in use by governmental authorities, international research communities and TSOs two types of combinations are used for the hybrid physical-statistical approach: (i) a combination of physical and statistical approaches (e.g., Zephyr model [96]); and (ii) a combination of models for the short-term (0 to 6 hours) and for the medium-term (0 to 48 hours) (e.g., UMPREDICTION project [97].

A different approach is the combination of alternative statistical models. One example of that is the Spanish Sipreólico [98]. The combination is achieved through the use of the horizon as a criterion after the model that best suits each horizon is identified off-line or by a selection process based on the recent performance of each individual model [41].

In this thesis the last mentioned example is followed up. Since the Kalman filter procedure brings better results for the first five hours of prediction, the Q-Learning algorithm is beneficial for the longer-term forecasting (till 24 hours), a new combined approach is developed to unify both of these advantages. In order to show the performance of the combined approach the input data from the year 2006 is taken. Thereby the first 180 days are used for learning within the Q-Learning approach; the rest of the year (174 days) is used for the actual prediction and its evaluation. Figure 4-19 presents the results.

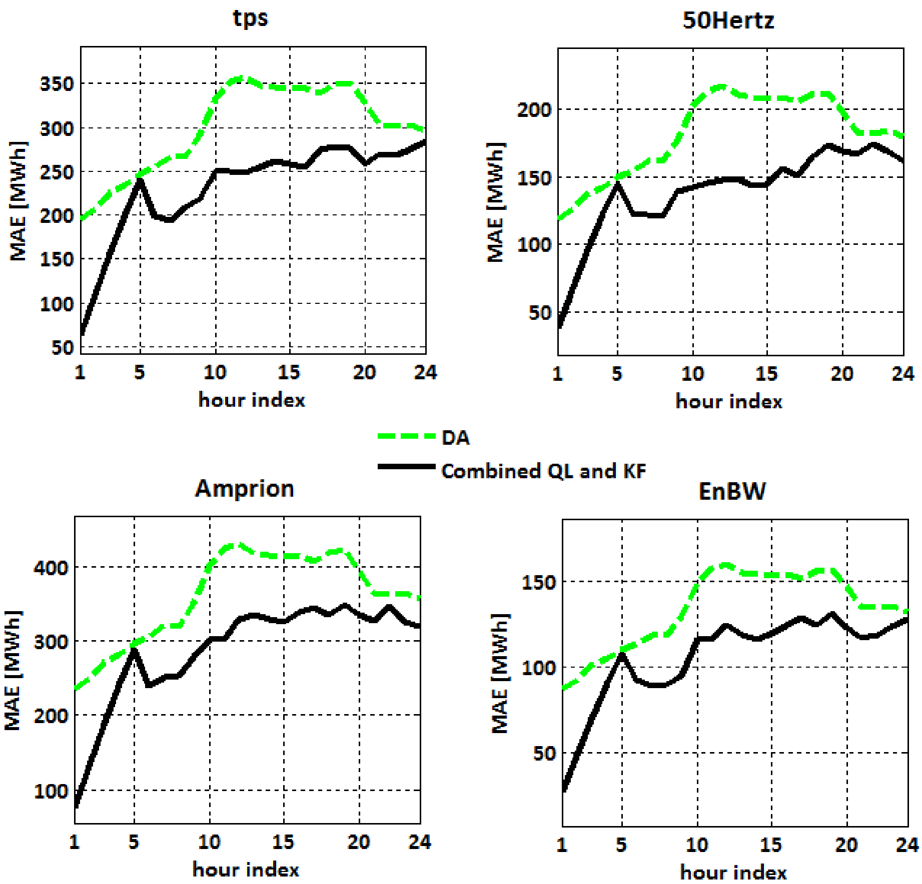

Figure 4-19: Performance of combined approach in comparison with the initial day-ahead forecast

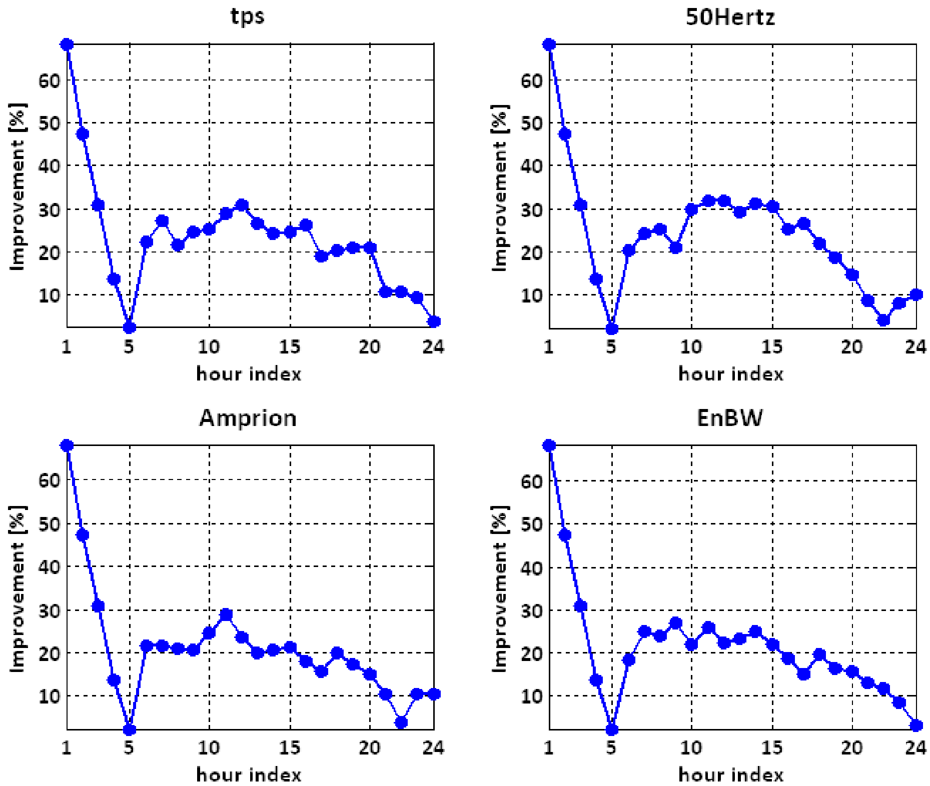

Figure 4-20: Improvement of the initial day-ahead forecast by combined approach

If the combined approach is applied to the best learning/prediction time frames (here for 50Hertz), calculated in section 4.2.4, the improvement is more obvious (Figure 4-21, see either Figure 4-7 for comparison).

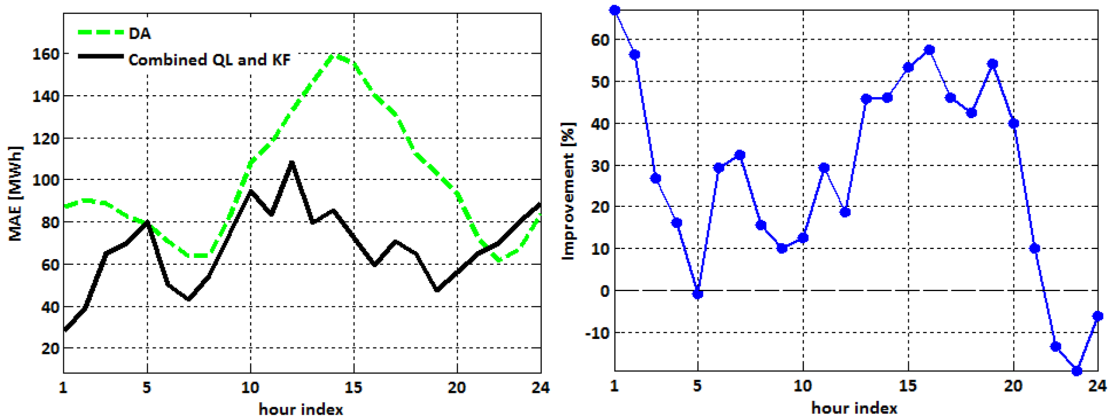

Figure 4-21: Application of the combined approach to the best calculated combination of learning/prediction time frames of Q-Learning (data base 2006)

Chapter 5

Algorithm validation

In order to generalize the achieved results as well as to describe application specifications of the used optimization methods following section is introduced. It analyzes the potential optimization abilities of the applied approaches, whereas the main attention is dedicated to the Q-Learning method.

5.1 Introducing remarks

It is important to evaluate the error measures, proposed in the previous section, on data which has not been used for constructing the prediction model or for tuning some parameters of the method.

Training (or estimation) error does not provide a good estimate of the test error, which is the prediction error on new (independent) data. Training error consistently decreases with model complexity, typically dropping to zero if the model complexity is large enough. In practice, however, such a model will perform poorly, and this will be clearly seen from the performance for the test period [40].

The capability to provide adequate predictions on new and independent test data is usually known as generalization, and its importance in assessing the quality of forecasting methods is crucial because it translates the ability of the method to predict under different circumstances. Therefore, it is very important to evaluate the error measures on data that has not been used to build the prediction model or to tune the method's parameters.

In order to achieve this, the data is usually divided into two different sets, according to their time characteristics: (1) the training dataset, and (2) the testing dataset (see Figure 5-1). The training dataset is used to build the model, taking into consideration the validation of decisions and/or rules on the model’s structure. However, since the training dataset does not provide adequate estimates for the prediction errors, it is necessary to use new and independent data — the test dataset. Thus, prediction models should be developed and tuned by using the training data and disregarding the test data, while the error measures should be based on the test data only [40],[41].

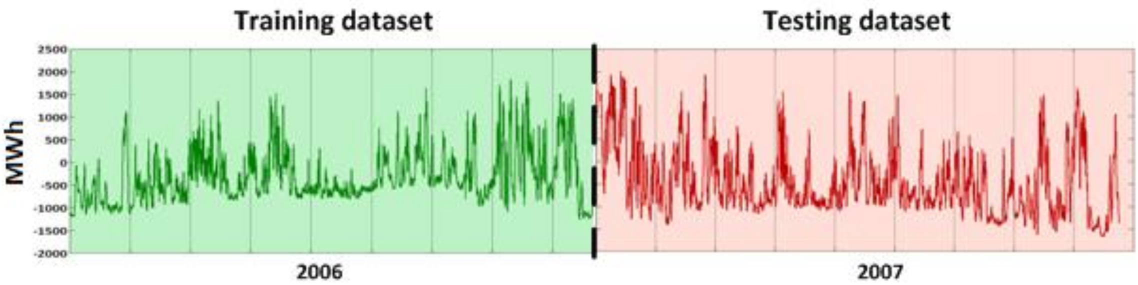

Figure 5-1: A dataset from the wind power feed-in in the control area of 50Hertz split into a training and a testing dataset

5.2 Algorithm performance study

Following section analyses the performance of the optimization methods. The purpose is to validate the algorithms’ ability to improve the initial day-ahead forecast.

With respect to the KF it was already shown that its major contribution to improvement of initial day-ahead forecast consists in the prediction enhancement in the first hours. It must not necessarily be the morning hours; the method can be applied autonomously disregarding the time. Due to its linear estimation characteristics it benefits from the available “real-time” values. The more distance between this initialization and the further time of prediction, the major the error this prediction is subject to.

Whereas analyzing the performance of the Q-Learning more possible ways of its application can be discovered. In the section 4.1.4 optimal intervals for learning/prediction for each TSO were investigated. These intervals were applied to test the performance of the Q-Learning during the whole period of available data (two years, 2006-2007). In order to achieve the uniformity of results for all four TSOs, the testing dataset (see Figure 5-1) was chosen as it is shown in Figure 5-2.

The goal was to analyze which hours are more likely to be over- or underestimated. The results are comprised of MAE for the optimal 10 days of prediction over the whole testing period and presented in Figure 5-3.

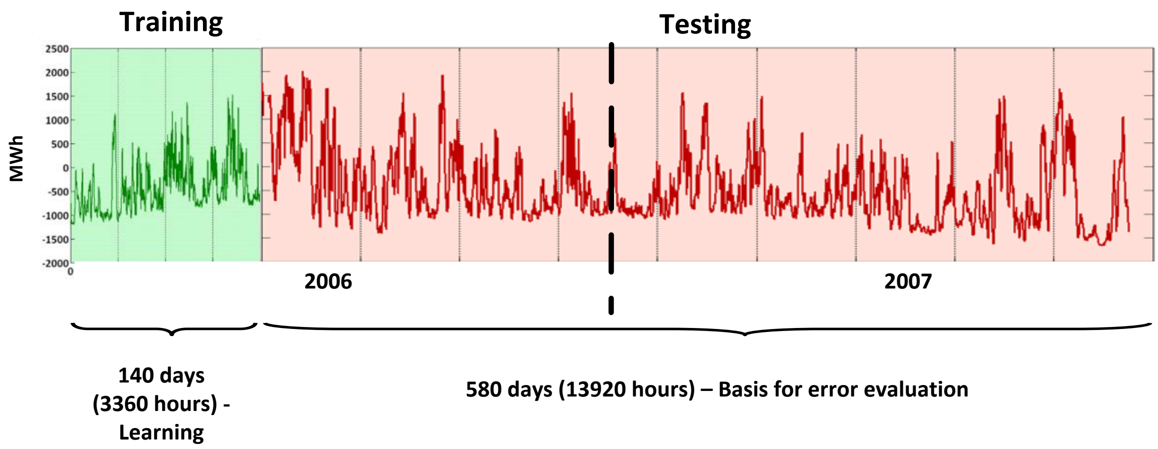

Figure 5-2: Datasets for analysis of performance of the Q-Learning algorithm

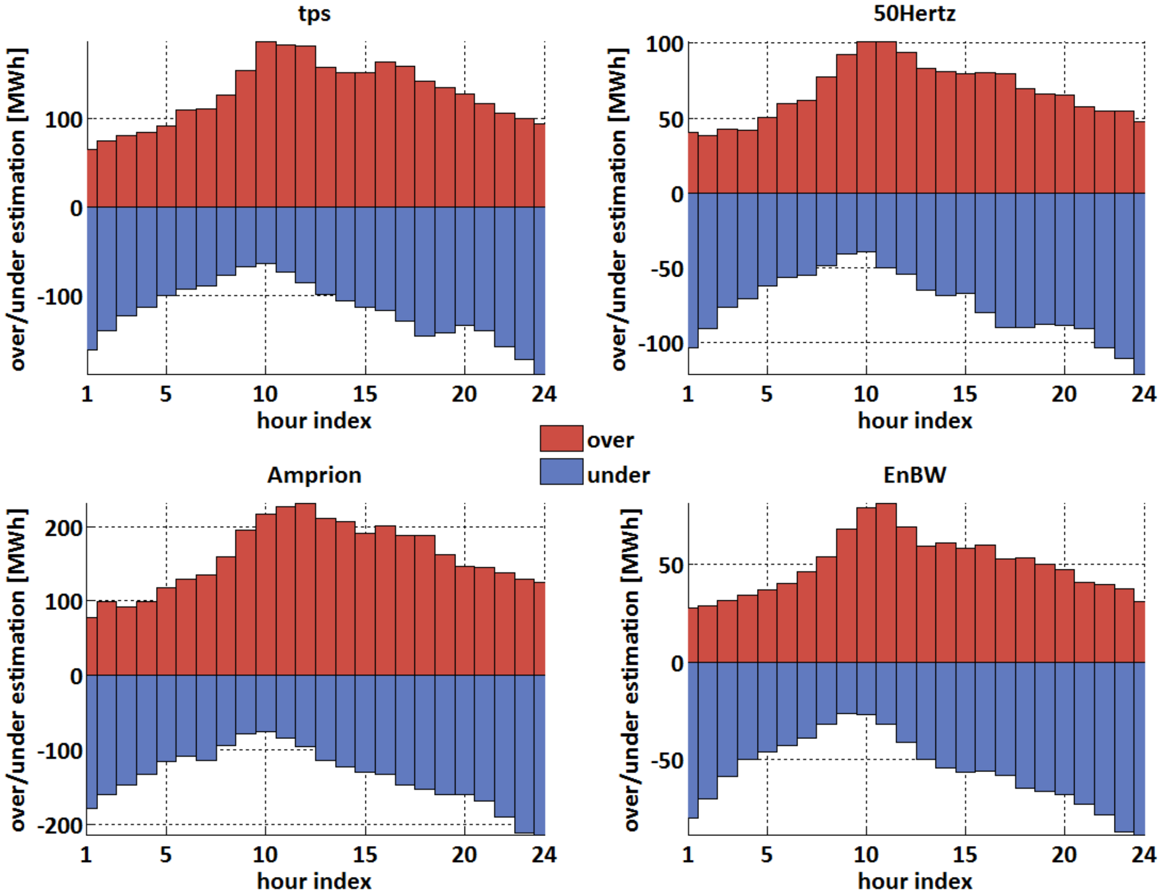

Figure 5-3: Over-/Underestimation by means of the Q-Learning

They are rather similar for each of four German TSOs. The reason is the relative equality of initial data (see e.g. Figure 3-5 to recall). It is further to notice that the rest deviations each TSO has are correlated with the volumes of wind power that is available in each control zone. So, e.g. Amprion that has the most wind power in its control area has the major rest deviations after optimization by means of the Q-Learning; EnBW as the TSO with the smallest wind power volumes has correspondingly the minimum error.

If all the deviations during the whole period of 24 hours are summed up (Figure 5-4 and Figure 5-5), it will be seen, that the greatest part of deviations (nearly 7% of the day sum) occurs at 12 p.m. in the case of underestimation and at 12 a.m. in the case of overestimation (see Figure). In general, the SVs are more likely to be underestimated at night hours (from 10 p.m. till 2 a.m.), whereas during the day the tendency is to overestimate the needed bidding volume (10 a.m. till 12 a.m.). This phenomenon takes place almost in the same manner at all four TSOs.

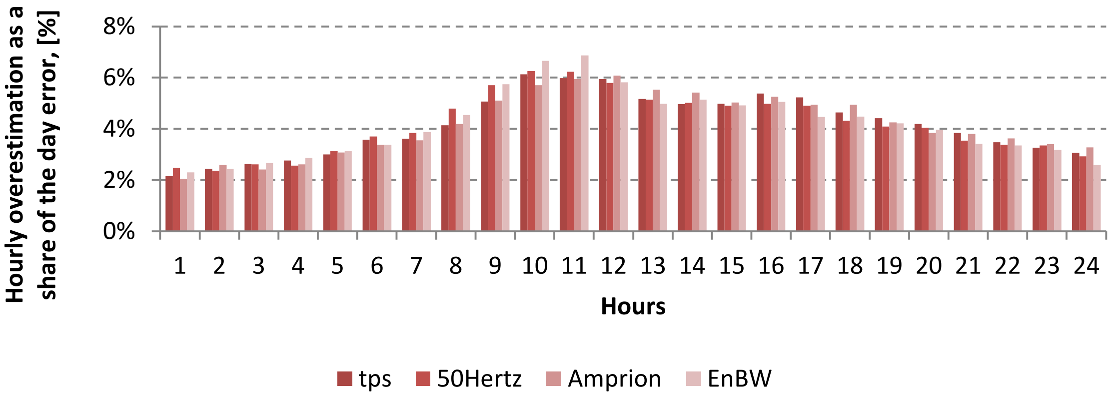

Figure 5-4: Share of individual overestimations within the day error (Q-Learning)

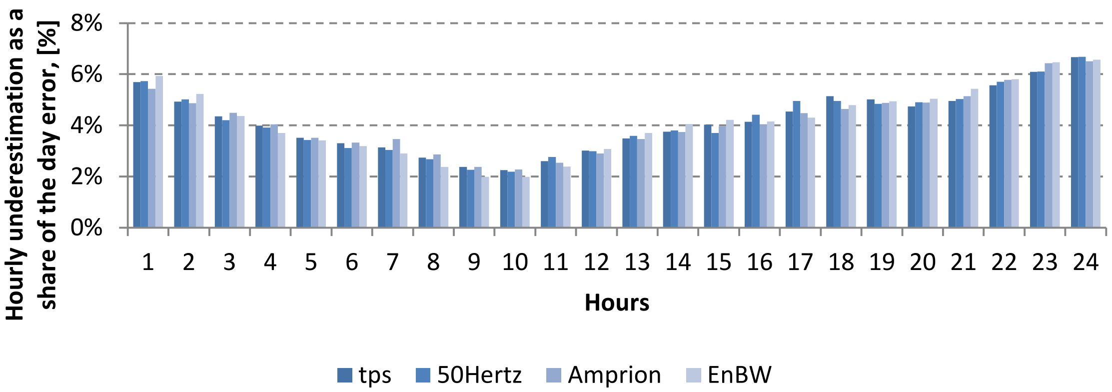

Figure 5-5: Share of individual underestimations within the day error (Q-Learning)

Underestimation is from the TSO operator's point of view is better for grid operation since in order to cover the difference to the forecasted data no additional power plants must be run up. Instead of that power reserves accumulated during the day (i.e. spinning reserves[64]) can be activated. Overestimation leads to more undesirable consequences on the day-ahead market such as not-commitment of some generations or imports and in real-time scheduling of more expensive generation. In the worst case more cost-intensive power plants must be run up. It is therefore important for the further application of the Q-learning method to assume these modelling peculiarities. In order to overcome this system error an offset can be applied.

[64] The spinning reserve is the unused capacity which can be activated on decision of the system operator (TSO) and which is provided by devices which are synchronized to the network and able to affect the active power [99]

In the next step it was investigated how often certain deviations occur if the best learning/prediction days' combination is applied for the whole period of available data basis (Figure 5-6). For each TSO's case its own best combination was used (see Table 4-1 to recall).

As it already could be assumed from the previous Figure the distribution of over- and underestimated SVs is to a certain extent identical: both positive and negative deviations are allocated in the similar manner. It means the approach do not possess the ability to favour one of the both prediction alternatives.

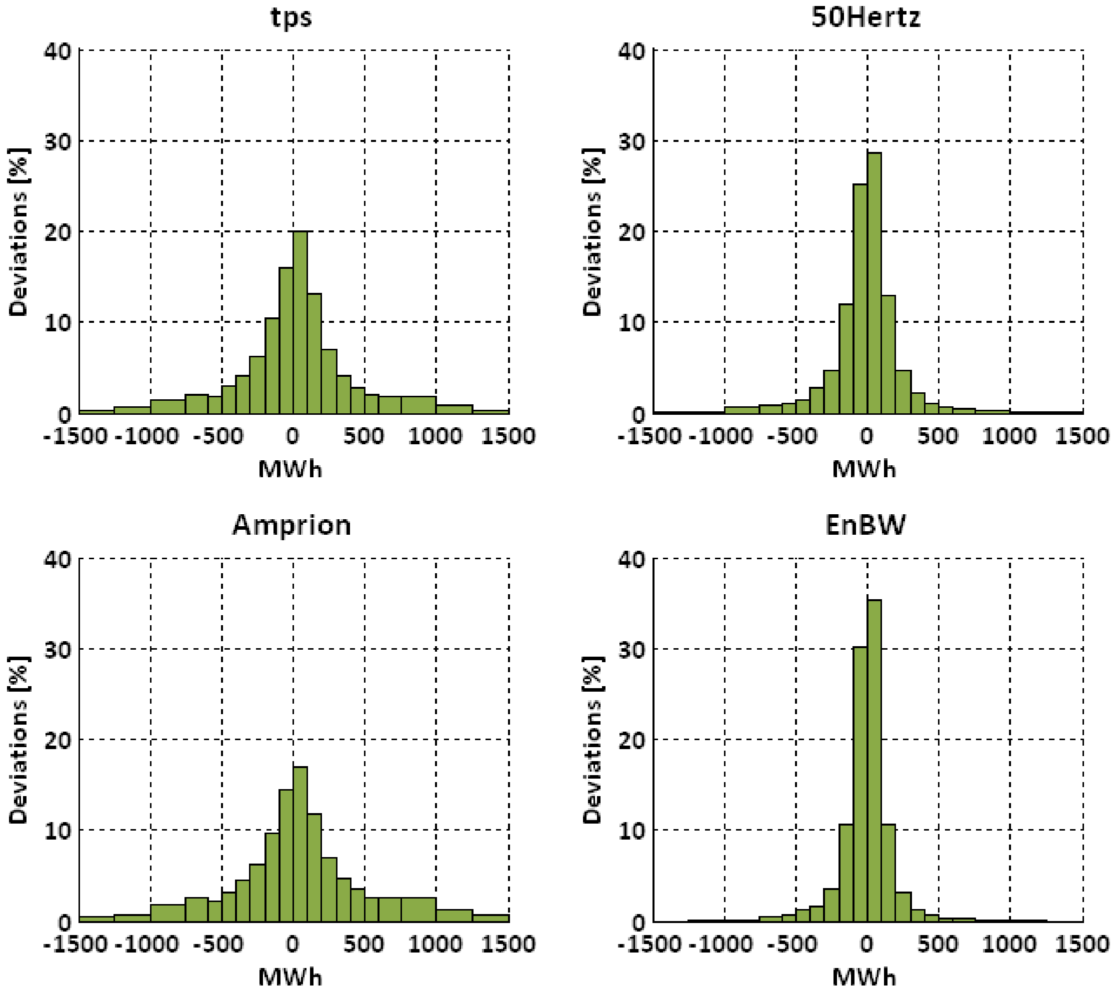

Figure 5-6: Distribution of deviations after application of the Q-Learning

Further, it is repeatedly to observe that the accuracy of the forecast by means of the Q-Learning is highly correlated with the wind power volumes a certain TSO has to trade with. Accordingly, the greatest spreading of prediction errors has a TSO with the maximum wind power in its control area, Amprion. On the contrary, EnBW, has the comparatively high quality of prediction, more that 35% of deviations in its case are within the limits of [0:100] MWh, almost 30% within the [-100:0] limits. 50Hertz is the TSO with the second-best results: almost 30% of its deviations do not exceed the value of 100 MWh, almost 25% are within the limits of [-100:0] MWh.

In further step prediction by means of the Q-Learning algorithm is presented in the context of month perspective (Figure 5-7). The goal is to investigate which role the seasonality obtains for predictions with the mentioned optimization method.

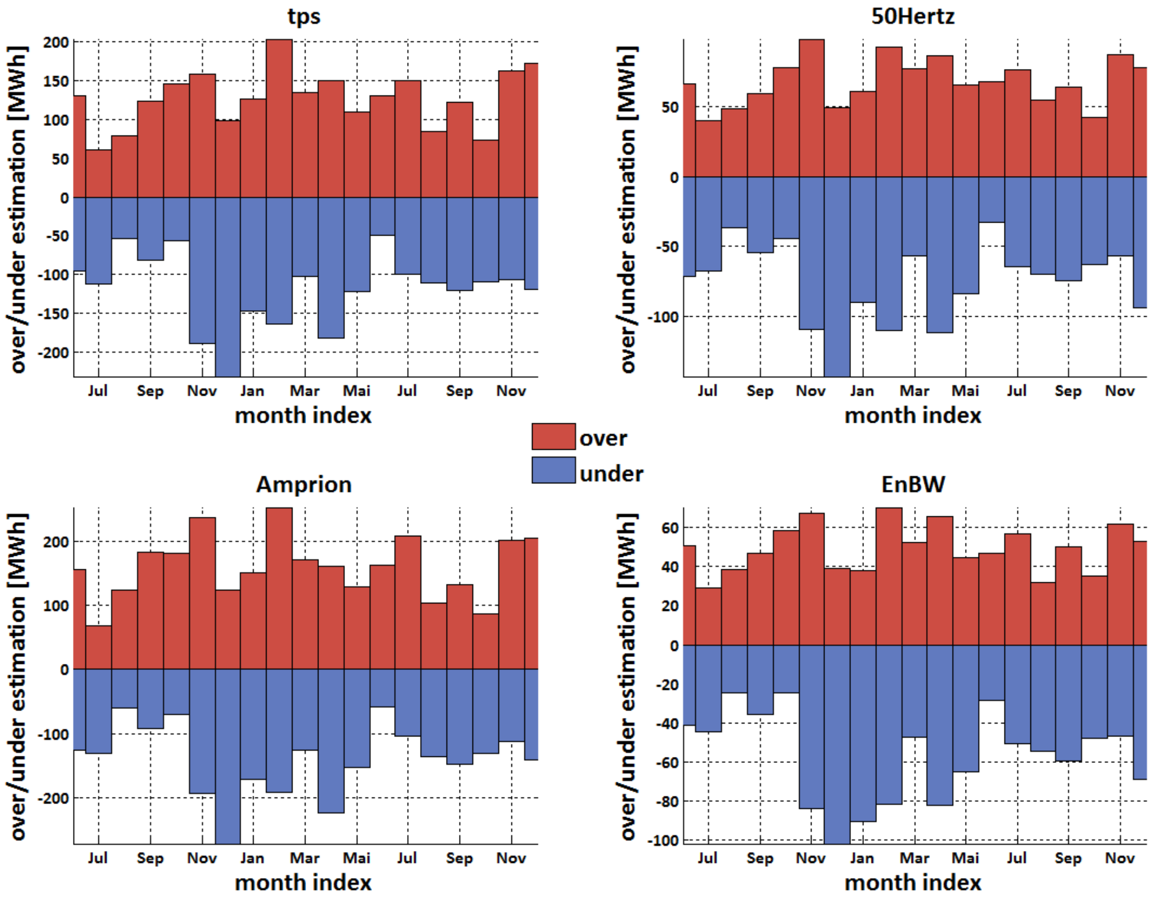

Figure 5-7: Over- and underestimation using Q-Learning. Month view

On the individual figures of each four TSOs, which are very similar again, it is to observe that July 2006 was the month with the minimum overestimation error. It concerns all four TSOs. Further in the case of three TSOs (tps, 50Hertz, Amprion) October 2007 exhibits the second-best result; August 2006 is the month with the third small overestimated deviation. Prediction results of EnBW vary from the rest: the second place in overestimation takes August 2007 and October 2007 is the month with the third-best result. In the case of underestimation again three of four TSOs (tps, 50Hertz, Amprion) show the same statistics: the first three best results in the underestimated deviations are June 2007, August 2006 and October 2006. In the case of EnBW these are August 2006, October 2006 and June 2007.

Considering the greatest prediction errors from the month point of view the results are not so uniform as before. In general months with the highest magnitude of overestimation are November 2006, February 2007, November 2007, and December 2007. The maximum underestimation occurs however in the same month in all fours cases – in December 2006.

Classified by days of the week the phenomenon of December 2006 becomes more obvious. On Figure 5-8 the results for the corresponding 4 weeks are presented. Underestimated values clearly prevail over overestimated ones. The difference is specifically to notice on Tuesday and Wednesday as well as on Saturday and Sunday.

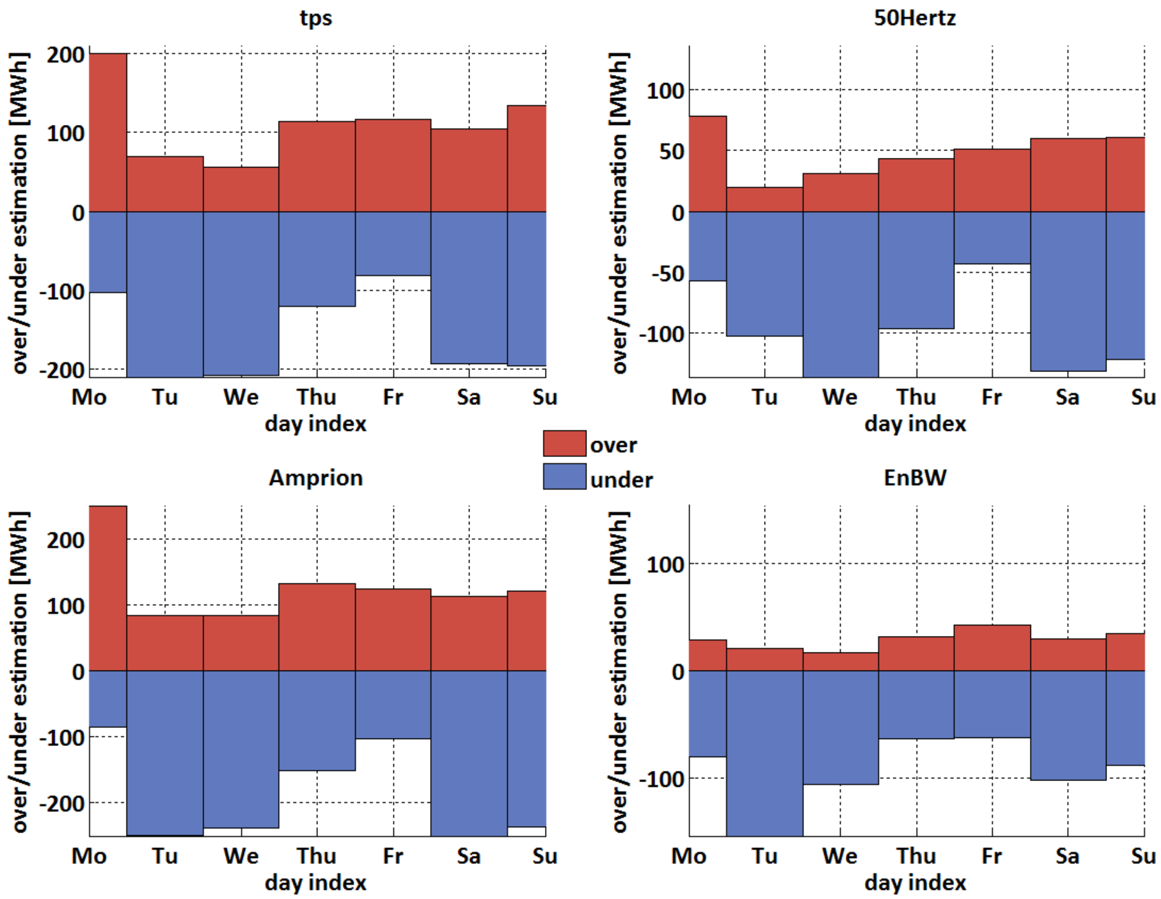

Figure 5-8: Over- and underestimation by means of the Q-Learning algorithm in December 2006. Week day view

The graphics of tps and Amprion are quite comparable because of the similarity of power volumes they have to sell on the power market. The same counts for 50Hertz and EnBW whose power capacities are smaller in comparison with two other TSOs and alike to each other.

It is evident that the seasonality has an important influence on the prediction results. Thus significant wind energy events as, i.e. abrupt changes in wind speed that characteristic for the autumn months lead to extreme and rapid changes in wind power output and this unforeseen circumstances increase the prediction error consequently. In the contrary, in summer, during the windless months the quality of prediction is significantly better.

In order to prevent such unfavourable characteristics of forecast, length of learning/prediction intervals can be adapted, i.e. changed from month to month. The adapted algorithm will then continuously explicitly learn peculiarities of winter/summer months.

Another possibility to avoid observable under-/overestimation is to use a fix offset for particular prediction period. It means i.e. in case of December 2006 to divide from sublimation values suggested by the Q-Learning algorithm 100 MWh (tps, Amprion) or 50 MWh (50Hertz, EnBW).

Chapter 6

Conclusions and outlook

6.1 Summary and conclusions

The points that are addressed in this thesis refer to the problems that a TSO faces with during its everyday operation. These problems do not belong to its core business (securing of reliable energy supply in the broadest sense), but to its new obligations emerged after adoption of unbundling regulations and conducted in accordance with the German governmental environment policy. The main question thereby is – how can the day-ahead trading of wind power be optimized if the only information available to TSO's market operator is the day-ahead forecast of wind power feed-in and its extrapolations ("real-time" values) that become obtainable 24 hours thereafter.

The methods proposed in this thesis can be defined as "post-processing" methods, since their main task is to improve the quality of already existent day-ahead wind power forecasts. Two optimization methods were presented – Q-Learning and the Kalman filter. The first was chosen because of its simple implementation and advantages, known from the price forecasting for energy markets. The second was an alternative to the first method in order to explicitly consider the stochastic nature of wind power feed-in in form of mathematical equations.

The great advantage of Q-Learning algorithm and the reason it was chosen as an optimization method is its independency of the model of the environment's dynamics. This dramatically simplifies the analysis of the algorithm and enables early convergence proofs. Its self-learning mechanism allows the operator to let the machine decide which policy should be followed in order to achieve the improved results. Thanks to its simple application and a finite number of states and action it does not require extensive calculation and thus can be implemented even on systems with limited computational capabilities (Figure 6-1).

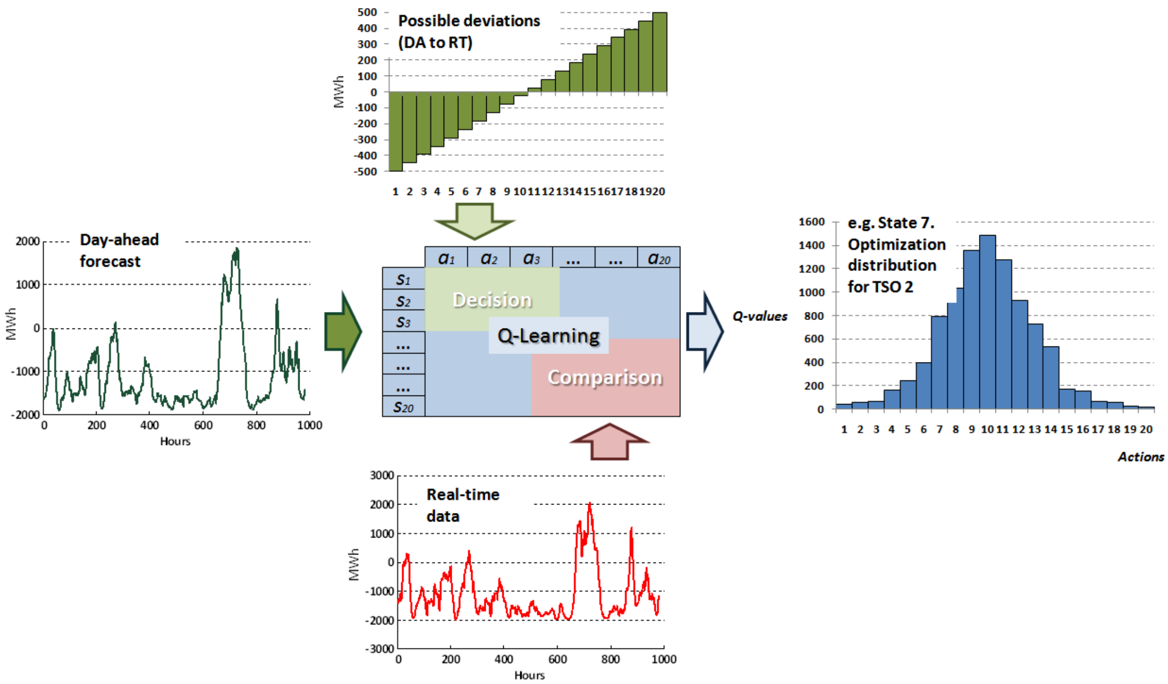

Figure 6-1: The Q-Learning method. The principal scheme

The resultant Q-table is a convenient guide for actions, where for each level of sublimation value the appropriate additional quantity for day-ahead trading is determined. Moreover the distribution of Q-values for a certain state can be used for risk evaluation of other possibilities (actions) for improving the day-ahead market performance.

For the improvement of the day-ahead forecast by means of Q-Learning following features are important to consider:

1) The number and distribution of state/action space. It must be modelled in accordance with actual amplitude of wind power feed-in/forecast deviations;

2) The algorithm should be tested on the optimal time horizons for learning/prediction;

3) Improvement of the Q-Learning performance can further be achieved through tuning of penalty function, learning rate, discount factor;

4) Prediction results can be improved if the learning/prediction intervals are updated continuously depending on the season/month.

Q-Learning as all reinforcement learning architectures are effective at trial-and-error learning, but not more. They can not do any of the things that are considered “cognitive”, such as reasoning or planning. They do not learn an internal model of the world's dynamics, of what-causes-what, but only of what-to-do (policy) and how-good-is-it (return predictions) [72].

This was the main reason for search of an alternative method that could cope with the dynamic characteristics of the input data. The Kalman filter was chosen because it is an efficient recursive filter that estimates the internal state of a linear dynamic system from a series of noisy measurements. Having considered the initial day-ahead forecast as such a measurement series it was expected to predict the state of the “real-time” dynamic system for each hour of a certain trading day (Figure 6-2).

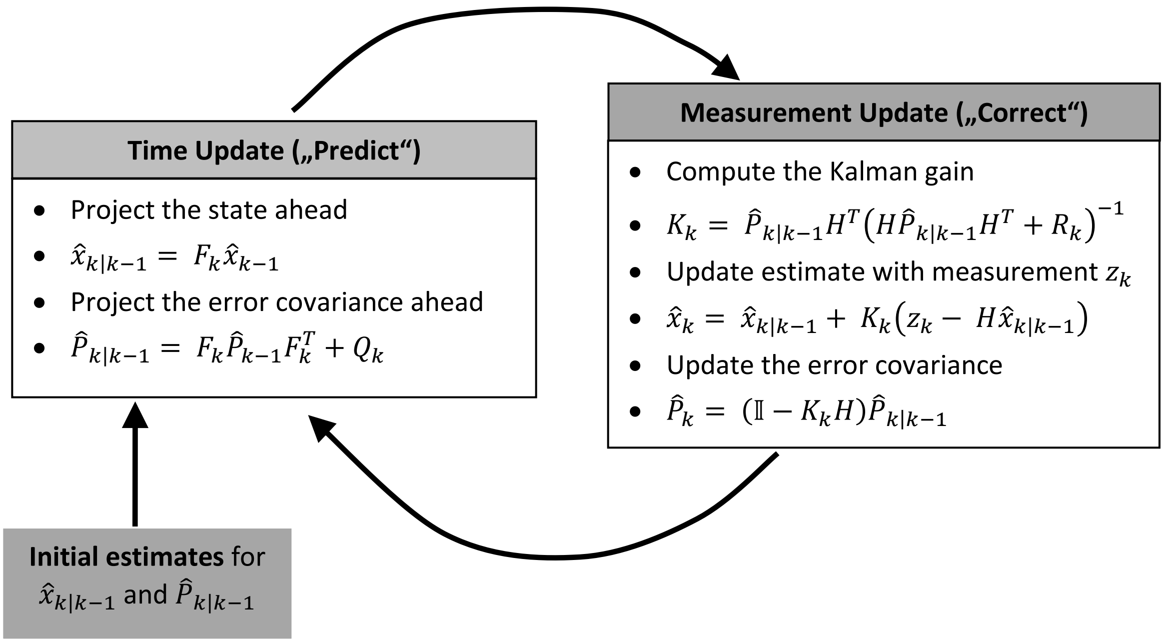

Figure 6-2: The Kalman filter method. The principal scheme

A correct description of the underlying process by means of two model equations of the Kalman filter (state and measurement equation) is the most challenging task in filter design. Further, the quality of Kalman filter performance depends largely on

- initial modelling parameters (accordance of the available data to the Kalman filtering framework);
- the parameter estimation of the underlying dynamic system ($x_k, P_k, z_k F, H, Q, R$).

It is also worth to mention, that many real dynamical systems do not exactly fit the model proposed by the Kalman filter. In fact, unmodelled dynamics can seriously degrade the filter performance, even when it was supposed to work with unknown stochastic signals as inputs. The reason for this is that the effect of unmodelled dynamics depends on the input, and, therefore, can bring the estimation algorithm to instability (divergence).

In this thesis the day-ahead forecast considered as a series of noisy measurements do not fit the requirements set by the Kalman filter. Notwithstanding that the significant improvement brought by the Kalman filter in the first hours of a day gives this method the chance to be implemented by a TSO.

Performance of Kalman filter in the later hours can be improved if weighted with the initial day-ahead forecast. The weighting prevents the linear approximation of the algorithm to distort the prediction results. It is further advantageous for the method's prediction quality if the "real-time" values are available in shorter time lags (less than 24 hours).

The favourable characteristics of both optimization methods can be further emphasized if combined.

As shown in the thesis presented optimization methods satisfy the requirements declared at the beginning completely. The methods are:

- embedded in a simulation model which corresponds to the RES regulatory framework in Germany;

- modelling assumptions gave the possibility to overcome the obstacles of limited input information;

- different market strategies can be tested with the help of predicted sublimation values (an operator can fully trust to the predicted values or choose the second-best variant, a fix offset can be applied if some over/underestimation is expected etc.);

- initial modelling assumptions can be easily changed in accordance with actual user needs.

Improvement of the TSO's forecast ability brought by presented optimization methods leads to:

- Cost savings due to decreased amounts of control energy to be provided;
- Reduced imbalance charges and penalties;
- Competitive knowledge advantage in day-ahead and intraday energy market trading.

6.2 Further research

Besides further development of proposed optimization methods further topics relevant for TSO's market performance are interesting to be investigated.

New RES legislation

As mentioned before, the RES legislative regulation has been changed during the writing of this thesis. Consequently, the quantities of wind power feed-in were increased that a TSO has to sale on the energy market. It is therefore important in the further research step to test the performance of used methods on this new real-world data. It is may be the case that the allocation of state/action space may have to be adjusted; new optimal time horizons for learning/prediction periods may have to be defined (for Q-Learning), P_k, F, H, Q, R –matrices may have to be adjusted (for Kalman filter).

Assuming new legislative restrictions are coming into the field of the day-ahead trading (i.e. marketing of all received RES power quantities regardless their volumes) necessity to predict the wind power volumes for the next 24 hours becomes redundant. All the more the proposed optimization methods must be used for **intraday trading**. The most important factor that has to be considered within the methods' adaptation is the short-term availability of "real-time" values of wind power.

Uncertainty forecasting

The complexity of the weather will probably never allow for perfect wind power forecasts leaving always a risk in trusting the forecast. It is therefore important to provide the end-user (in this case - a TSO, but even more end-users can gain from improved WPF as well) with additional information concerning the specific forecast situation to enable an assessment the risk of relying on the wind power forecast. This additional information may contain the information about uncertainty of a certain single value for each look-ahead time. This uncertainty forecasting may be expressed in the form of probabilistic forecasts or with risk indices provided along with the traditional point predictions. It can be shown that any decision related to wind power management and trading cannot be optimal without accounting for prediction uncertainty. The first studies devoted to this subject have shown that reliable estimation of prediction uncertainty allows wind power producer to significantly increase their income in comparison to the sole use of an advanced point forecasting method. Other studies of this type deal with optimal dynamic quantification of reserve requirements, optimal operation of combined systems including wind, or multi-area multi-stage regulation. More and more research efforts are expected on prediction uncertainty and related topics.

Ramp events

To date the majority of work on the uncertainty of wind energy forecasts (this thesis as well) has been focused on the possible amplitude of wind production that might occur at a given time. However, there has been limited investigation into effectively defining the possible timing of significant wind energy events, called ramp events. Wind ramp events are extreme and rapid changes in wind power output due to abrupt changes in wind speed. The severity of the large deviation depends highly on how fast it happens, and on the timing especially if concurrently other events happen (i.e. the electricity demand is also highly fluctuating).

There are two ways in which variation in wind speed can result in a rapid change in power production: ramp up wind speed and high wind speed. At ramp up wind speeds the power output of a wind turbine is highly dependent on wind speed, and rapid changes in wind speed will therefore cause rapid changes in power. At high wind speeds a smaller increase in wind speed can trigger high wind speed shutdown, causing a rapid drop off in power production. The majority of ramps are caused by rapid changes in ramp up wind speed, but high wind speed shutdown events are also significant.

Ramp events occur rarely, but unexpected rapid changes in power from wind farms can be problematic for TSOs, and the impact of ramp events grows as the penetration of wind energy continues to increase. The difficulties presented by periods of rapid change are consequently passed on to the energy trading in the form of a lowered overall market value of wind energy. With accurate prior warning of a large ramp event and information about its widening within a certain area, energy from other sources may be scheduled in order to mitigate a steep rise or drop in wind energy. This means the accurate forecast of ramp events and quantification of ramp forecast accuracy is crucial to the large-scale integration of wind energy into electricity grids, and also to help TSOs better understand the risk involved in energy trades at times of high variability. Nowadays it is a future challenge to improve the forecasts for such situations [100], [101].

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Appendix A

Assumptions and corresponding exemplary calculation of HE allocation key and exchanged wind power quantities in order to avoid the lack of necessary data

1) Individual shares of each TSO on the relevant parameter

For calculation of the individual shares of each TSO on the relevant parameters the respective amounts, published in the annual TSO's reports are taken. Based on the sum of these amounts, the individual share of a TSO on each relevant parameter is determined. It is subsequently assumed, that the share of each TSO on the relevant parameter does not significantly change during one year.

Table A-1 and Table A-2 show an exemplary calculation.

Table A-1: Shares of German TSO's on final electricity consumption (calculated on the basis of annual reports of 2007)

	Final electricity consumption (FEC)			
	Total [GWh]	*Share [%]*	*Thereof privileged in terms of §40 EEG 2009 [GWh]*	*Share [%]*
tps	147.177,09	29,7%	15.425,79	21,4%
50Hertz	94.586,30	19,1%	15.983,02	22,2%
Amprion	189.071,90	38,2%	35.390,20	49,1%
EnBW	64.205,20	13,0%	5.250,78	7,3%
Sum:	**495.040,50**	**100%**	**72.049,79**	**100%**

Table A-2: Shares of German TSO's on RES-feed-in (calculated on the basis of annual reports of 2007)

	RES-infeeds			
	Total [GWh]	*Share [%]*	*Thereof privileged in terms of §40 EEG 2009 [GWh]*	*Share [%]*
tps	26.340,44	39,4%	110,84	21,8%
50Hertz	21.704,34	32,5%	112,69	22,2%
Amprion	14.180,22	21,2%	245,84	48,5%
EnBW	4.577,93	6,9%	37,946	7,5%
Sum:	**66.802,93**	**100%**	**507,31**	**100%**

2) Monthly amounts on the relevant parameters for each control area

These amounts are calculated through the multiplication of the previously defined shares and the nationwide total values for these parameters, which are available monthly:

$$Monthly\ amount_{i,p}[GWh] = Nation - wide\ value_p[GWh] * Share_{i,p}[\%]\ , \qquad \text{(A.1)}$$

where the index p stands for "parameter", i - for individual TSO. An example for calculation of these monthly amounts is presented in Table A-3. The "deemed" special FEC is determined in accordance with Eq. (3.2). The calculation in Table A-3 is performed as an example for November 2008.

Table A-3: Monthly amounts of the relevant parameter for each TSO (calculation example for November 2008)

	FEC, [GWh]	**priv. FEC, [GWh]**	**„deemed" special FEC, [GWh]**
tps	12.788,24	1.331,72	45,60
50Hertz	8.218,62	1.379,83	46,37
Amprion	16.428,49	3.055,26	101,15
EnBW	5.578,80	453,30	15,61
Total nationwide, month value [GWh]	**43.014,15**	**6.220,11**	**208,74**

3) HE allocation key

The reference value for the calculation of the HE allocation key and the key per se are then determined according to the Eq. 3.1 (Table A-4).

Table A-4: HE allocation key (calculation example for November 2008)

	Reference value [GWh]	**HE allocation key [%]**
tps	11.502,13	31,1%
50Hertz	6.885,16	18,6%
Amprion	13.474,38	36,4%
EnBW	5.141,11	13,9%
Sum:	**37.002,78**	**100,0%**

Table A-5: Calculation of exchange quantities within the HE

Horizontal equalisation							
To / **From**	Wind energy feed-in on 05.01.2008 from 00:00 till 01:00	tps	50Hertz	Amprion	EnBW	**Sum Transferred**	Nation-wide
	[MWh]	*[MWh]*	*[MWh]*	*[MWh]*	*[MWh]*	*[MWh]*	*[MWh]*
tps	3955		735,63	1.439,62	549,75	**2.725,00**	-910,31
50Hertz	4148	1.290,03		1.509,87	576,57	**3.376,47**	-2.327,06
Amprion	1611	501,02	299,65		223,93	**1.024,60**	1.952,56
EnBW	76	23,64	14,14	27,66		**65,44**	1.284,81
Sum Received		**1.814,69**	**1.049,41**	**2.977,16**	**1.350,25**		**0,00**

As it seen from Table A-5, tps and 50Hertz give up the excessive power, they can not consume within their control areas; other two TSOs, Amprion and EnBW receive these additional amounts in order to cover their higher final consumption.

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Theses

1. Growth of renewable energies in German energy-mix, unbundling regulations and German environmental legislation have changed the traditional role of a Transmission System Operator (TSO) as of provider of ancillary services to ensure network stability, further responsible for congestion prevention and management, ensuring the system availability.

2. In its new role of coordinator of renewable energy sources (RES) balancing group within the Nationwide Equalisation Scheme (EEG-Ausgleichsmechanismus) the TSO takes responsibilities for marketing of stochastic wind power on the day-ahead spot market of the energy exchange.

3. In order to market received wind power quantities the TSO needs a high quality of day-ahead wind power forecast (WPF). This service is provided by corresponding organisations. However, prediction error contained in the WPF is still significant and results in millions of Euro additional costs. These expenditures become then a burden for final electricity customers.

4. In order to decrease the prediction error connected with the WPF the TSO receives as a service two optimization methods (Q-Learning and Kalman filter) are presented. They are defined as “post-processing” optimization methods since their application occurs after the initial day-ahead prediction. Their goal is to improve the quality of the initial day-ahead forecast.

5. To obtain the necessary modelling data the Nationwide Equalisation Scheme was simulated. Thereby specific modelling assumptions were made in relation to simulation of the horizontal equalisation process.

6. The resulted modelling data contains two time-series: the initial day-ahead forecast of sublimation values (wind power quantities to be market on the day-ahead spot market) and the “real-time” values (online estimation data, available to the TSO with the time lag of 24 hours).

7. The Q-Learning algorithm, which is a reinforcement learning method, improves the initial day-ahead forecast, especially in the noon hours. For the proper performance specific learning/prediction intervals must be defined.

8. The Kalman filter is a set of mathematical equations that provides an efficient computational (recursive) means to estimate the state of a process, in a way that minimizes the mean of the squared error. This method is especially effective in improvement of early morning hours of the initial WPF.

9. The favourable characteristics of both optimization methods can be further emphasized if combined