Multi-objective Wind Farm Control

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Link to article, DOI:
10.11581/dtu:00000044

Publication date:
2019

Document Version
Publisher's PDF, also known as Version of record

Link back to DTU Orbit

Citation (APA):
Multi-objective Wind Farm Control

Dissertation

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DTU Wind Energy
December 2018
Abstract:
A framework of an operational wind farm controller is developed in this work comprising solutions for power control and induction-control of wind farms, including measurement-processing procedures and integrated turbine control. The major advantages of the framework are faster prototyping, design flexibility and a common environment for the development of wind farm control. The measurement-processing unit comprises, amongst other, advanced procedures for the accurate quantification of wind conditions. Particularly, the measurement of turbulence was investigated with respect to the impact of the spatial variance of the second-order moment of correlated wind speeds. The first analytical solution for the quantification of the spatial variance was developed and successfully verified in this thesis. The mitigation of the impact of the spatial variance on wind farm control, the verification of wind turbine performance, and sensor verification is investigated. Thereafter, three, novel developments for power control of wind farms are presented. First, a control-oriented, dynamic, linear model of wind farm flow and operation is investigated. The developed approach allows to model the future, control-dependent evolution of wind farm flow for its use in power control. The engineering model-based state space system results in a computationally fast execution. The dynamic simulation of a two-turbine array illustrates the main characteristics of the model, and the application to a large-scale wind farm demonstrates its scalability and performance in a more realistic setting. Second, the first model-predictive dispatch for power control of wind farms is successfully developed. The approach performs flow model-predictive optimization of farm operation according to multiple objectives and uses closed-loop feedback control to track the reference total power. Dynamic simulations demonstrate reduced fatigue loads and power variability, and more accurate tracking of the reference total power, as compared to present, standard power controllers. Third, the mitigation of fatigue loads of wind turbines is investigated using a novel database-driven approach which accounts for the turbine operation-dependent aerodynamic interaction of wind turbines. The approach is incorporated into a model-predictive power controller. Dynamic simulations on an eight-turbine array show a significant reduction in the sum fatigue loads of wind turbines. Finally, the impact of induction-control in nominal operation is investigated with respect to fatigue loads and the effect of external conditions on power. Large-eddy simulations show that a positive offset of pitch angle yields a beneficial reduction of the sum fatigue loads of a two-turbine array. The approach therefore allows for the trade-off between power production and fatigue loads in nominal wind farm operation. The investigation of a wide range of external conditions using the sDWM and recalibrated Larsen model showed the largest, potential power gain in low turbulence intensity and turbine spacing, and a wind direction aligned with the wind turbines. Even in the potentially most beneficial conditions, large-eddy simulations showed a reduced total power production. In the ensuing chapter, a turbine controller is presented that can enable the use of induction-control in wind farms. The suitability of the developed turbine controller is successfully demonstrated on a single wind turbine, and in a wind farm set-up in interaction with the wind farm controller.
Acknowledgements

I am grateful for the opportunity to undertake my PhD studies at DTU Wind Energy. Particularly, I would like to thank the supervisors of my studies, Dr. Nicolaos A. Cutululis, Dr. Michael Courtney, and Dr. Gregor Giebel for their advice and support. I am grateful for the academic guidance, fruitful discussions and broad support of Dr. Nicolaos A. Cutululis. I am also very grateful for the supportive guidance and the joint development of new project opportunities with Dr. Michael Courtney. Further, I am grateful for the fruitful discussions, support and guidance of Dr. Gregor Giebel. I would also like to thank Head of Section Dr. Jens Carsten Hansen for his support throughout the PhD studies and for his professional advice.

I would also like to thank for the exciting external stay at the National Renewable Energy Laboratory (NREL), US. I am grateful to Dr. Paul Fleming for inviting me to NREL and would like to thank him for the inspiring discussions on new developments on wind farm control. I am also grateful for the nice collaboration with and great support of Dr. Jennifer Annoni throughout my stay. Moreover, I would very much like to thank Prof. Dr. Lucy Pao for her advice, and particularly, for inviting me to share my work with her group. Furthermore, I would like to thank Dr. Jason Jonkman for introducing me to the FAST.Farm tool, even prior to official release, and the fruitful discussions around it. I would also like to thank Dr. Christopher Bay for the fruitful discussions and advice.

The industrial partners Siemens Gamesa Renewable Energy and Vattenfall are gratefully acknowledged for sharing their fruitful advice and data. I would further like to thank the team of Wind Master Technology, and Anemo Analytics for the fruitful, inspiring collaboration on the submitted WISDOM project proposal. I would also like to thank the partners of the Wind Farm Control Trials project for the good collaboration. Thanks to the Carbon Trust, EnBW, E.ON, Equinor, innogy, SSE, Vattenfall, ECN, Frazer-Nash and Windar Photonics.

Furthermore, I would like to thank Dr. John Olav Tande and Dr. Karl Merz for the inspiring collaboration on wind farm control and the joint contributions to the DeepWind conference.

From DTU Wind Energy, I am very grateful to Prof. Dr. Jakob Mann for his sustained advice and collaboration on novel insights on the measurement of turbulence.
Further, I would like to thank Dr. Mahmood Mirzaei, formerly at DTU, for the fruitful collaboration on development of novel turbine controllers and their use for wind farm control. Furthermore, I would very much like to thank Elliot Simon for the very nice collaboration in the Wind Farm Control Trials project and the development of the WIS- DOM proposal. I would like to thank Dr. Tuhfe Göçmen for the discussions on flow modelling in wind farms. Moreover, I would like to thank Torben J. Larsen, Christos Galinos and Albert Meseguer Urban for the sustained and extensive collaboration on the development of new methods for quantifying fatigue loads in wind farms. Last but not least, I would like to thank Dr. Matti Koviso, Dr. Kaushik Das, Dr. Gunner C. Larsen, Dr. Søren Juhl Andersen, Dr. Alan W. H. Lio, Dominique P. Held, Dr. Paul van der Laan, and Dr. Kurt Schaldemose Hansen for the good collaborations on various topics.

I would like to say special thanks to Prof. Dr. Poul E. Sørensen, Prof. Dr. Carlo L. Bottasso and Prof. Dr. Johan Meyers for being examiners of this thesis. I highly appreciate the time they devoted in reading the manuscript.

Finally, I would like to thank my friends for their kind support.

Jonas Kazda
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Acronyms

ABL  atmospheric boundary layer.
BEM  blade-element-momentum.
CFD  computational fluid dynamics.
CPC  ‘Constant Pitch Controller’.
CTSRC  ‘Constant Tip-speed Ratio Controller’.
D  turbine rotor diameter.
DEL  damage-equivalent load.
DFP  Dynamic Flow Predictor.
DTU  Technical University of Denmark.
DWM  dynamic wake meandering model.
EU  European Union.
IEC  International Electrotechnical Commission.
LES  large-eddy simulation.
LOS  line-of-sight.
MPC  model predictive controller.
MPO  model-predictive optimization.
MPPT  maximum power point tracking.
NREL  National Renewable Energy Laboratory, US.
NRMS  normalized root-mean-square.
O&M operations and maintenance.

PI proportional-integral.

RANS Reynolds-averaged Navier-Stokes.

RMS root-mean-square.

SCADA Supervisory Control And Data Acquisition.

sDWM standalone Dynamic Wake Meandering.

SGS sub-grid scale.

sPossPOW static PossPOW.

STD standard deviation.

SWF SimWindFarm.

TSR tip-speed ratio.

UTM Universal Transverse Mercator.
Chapter 1

Introduction

Whilst the worldwide energy consumption has been growing relentlessly, electricity production from renewable resources has grown rapidly in the past decades, with the objective to reduce production based on fossil fuel. Advantages attributed to renewable resources are sustainability and environmental friendliness, particularly significantly lower greenhouse gas emissions. Moreover, ensuring the security of supply of fossil fuels has come with high economical and political costs. The resulting political willingness to foster the use of renewable resources has driven the development and deployment of technologies for renewable electricity production. The most prominent ones are wind energy and photovoltaic energy.

As such, for wind energy, the levelized-cost of electricity has decreased by 25% from 2010 to 2017 [2]. The global, installed capacity has grown rapidly by 172% reaching 539,123MW in 2017. In the European Union (EU), the installed capacity amounts to 168,700MW in 2017 generating 11.6% of the EU’s electricity demand [3]. Denmark stands out with an average share of 44% of electricity production from wind energy [4]. The global, annual investment in wind energy has reached 107 billion US$ resulting in 52.5GW of newly installed capacity [3]. Electricity production from wind energy is therefore seen as a promising technology with increasing importance that avoids the economical, environmental, and political challenges associated with production from fossil fuels.

The World Energy Outlook [5] published by the International Energy Agency in 2017 projects a growth of the world’s primary energy consumption of 30% from 2017 to 2040. Additionally, the share of electricity in the end-use of energy is expected to increase further. It is projected that 40% of the rise in demand for electricity can be met from renewable resources. Albeit, past developments and future projections indicate that we are far from achieving a fossil-free use of primary energy until 2040, the numbers show a clear imperative to invest into the deployment and development of technologies for electricity generation from renewable resources.
1.1 Multi-objective Wind Farm Control

This section [1.1] is based on publications [J1, J3, J4, C2, C3, C4, C5].

To leverage economies-of-scale, wind turbines are typically clustered in wind farms. The thereby resulting aerodynamic interaction of wind turbines through wakes results in power losses of up to 30-40% and up to 80% higher fatigue loads [6]. As global installed wind power capacity increases, the mitigation of wake effects in wind farms is of more importance. Approaches for the mitigation of wake effects are investigated with respect to the design and control of wind turbines and wind farms. Design-related aspects are the optimization of the aerodynamics [7] and aeroelasticity [8] of wind turbines, and the layout of wind farms [9–12].

An advantage of mitigating wake effects using control is the applicability to existing wind farms. In turbine control, the modification of a turbine’s downregulation strategy is investigated in [13],[C1] to mitigate wake effects. In wind farm control, the reduction of wake effects is approached by the use of coordinated control of the operating point of wind turbines in a wind farm. Approaches of wind farm control can be categorized according to the operation mode of the wind farm, that is either (i) nominal operation or (ii) downregulated operation. In the latter, the objective is to follow a specified power for the total power output of the wind farm, while, optionally, reducing the fatigue loads for the wind turbines in the wind farm. Such wind farm control is typically referred to as power control.

1.1.1 Multi-objective Power Control

In power control, the accurate tracking of the reference for the total power of the wind farm is typically achieved by the use of a closed-loop feedback controller [14]. The total power demanded from the wind farm by the feedback controller is distributed to the wind turbines using a dispatch function [15]. The simplest dispatch approach is to distribute the total power to the wind turbines using a static distribution. Due to the variability of the available power of wind turbines this approach can result in a poor tracking of the total power reference. In [16] gain scheduling is proposed to mitigate the effect. Another approach is to distribute the total power to the wind turbines proportionally to the turbines’ available power [15].

An alternative control approach investigated in literature is model-predictive control [J4],[17–20]. The approach has three major advantages. First, it allows to optimize operation according to multiple objectives. As a result, the approach enables to not only follow a reference for the total power of the wind farm, but also to consider other objectives such as to reduce fatigue loads of wind turbines, and to lower the variability of turbine power. Second, model-based control can result in more informed control decisions, and hence potentially in an improved performance. For example, a model can provide the controller with information on the effect of a control action, that is a change in power set-point, on the future evolution of wind speed in the wind farm or on the fatigue loads of wind turbines. Typically employed models are thus dynamic models of wind farm operation [J3],[20,21] and models of turbine mechanical loads [J4],[17].
Third, model-predictive control allows to decide on the present control action considering the potential, future trajectories of operation. In [20] it is shown that accounting for the future dynamics of wind farm flow improves the control performance. Despite of these three advantages, there is two impediments to model-predictive control of wind farms. First, since model-predictive control is open-loop, the accuracy of tracking a demanding total power reference is expected to be poor due to the aerodynamic interaction of wind turbines through wakes [22]. Second, modelling the dynamics of flow in a large-scale wind farm is computationally challenging with many of present approaches. Amongst these, engineering models typically result in a faster computational speed. Using engineering models in [20, 23] resulted in a duration of the optimization in the order of minutes. Although remarkably fast, such duration still results in a delay in introducing the optimized control actions to the wind turbines.

To address these challenges, the present work introduces a model-predictive, closed-loop feedback controller including a computationally fast model. The controller is a synthesis of the investigated approaches for power control in literature, that is model-predictive control and closed-loop feedback control. The outer control loop is the closed-loop feedback controller that is commonly employed in present wind farms as introduced above. It ensures the accurate tracking of the reference for the total power of the wind farm, allowing it to operate in a mode that ensures available active power reserve to be used in ancillary services. In order to provide the advantages of model-predictive control described above, model-predictive optimization is used in the dispatch function of the closed-loop feedback controller. To reduce the computation time of the model-predictive optimization, a linear model is used, the DFP [J3].

A variety of dynamic models of wind farm operation are investigated in literature. These models are based on either engineering wake models [20, 24, 25] or two-dimensional computational fluid dynamics (CFD) [21, 26]. The latter models estimate hub height wind farm flow using customized, two-dimensional Navier-Stokes equations. A value proposition of such models is that wind farm flow is not only estimated at turbine locations, but in the entire hub height plane of the wind farm. The use of a CFD model is, however, typically more computationally expensive than the use of engineering models of wind farm flow. Engineering models have been investigated for model predictive control of wind farms, with good results that can perform wind farm-scale optimization in the order of minutes [20, 23]. In the quest of further reducing the duration of the optimization, a natural step is to move towards linear control approaches, such as linear model predictive control. To do so, one will need a linear, dynamic model of the wind farm flow. Few literature is available so far on this subject. The first, dynamic, linear model, the DFP, was successfully tested in [C3] on an eight turbine array. The DFP provides predictions of wind speed and power of wind turbines in a wind farm. The DFP is based on a linear state-space system and thereby is well suited for use in linear control methods. The use of engineering models and the linear nature of state-space systems results in a fast execution of the DFP. The performance of the DFP is evaluated in detail in [J3] and is used for model-predictive optimization and control in [J1, J4].

An alternative model that includes a dynamic turbine model, that is time-varying axial induction factors and yaw misalignments, and wake characteristics is presented in [27]. The estimation of turbine power using a linear model is, however, expected to result in
a larger error when used for power control of wind farms. Furthermore, the propagation of wind speed from an upstream turbine to a downstream one is modelled using a single delay step. Consequently, the model can currently only be applied to uniformly-spaced wind farms and the model sampling time is dependent on the ambient wind speed. These challenges are not present in the DFP. First, more accurate modelling of turbine power is enabled by the use of the turbine power set-point as a model input. As a result, the power output can be directly obtained from the power set-point constraint by the turbine’s available power. Second, in the DFP the propagation of wind speed is modelled using multiple delay steps. Thereby, the DFP can be applied to arbitrary layouts of wind farms and used with a desired sampling time.

Next, in this thesis, a new approach to reduce fatigue loads of wind turbines is introduced for use in power control. The approach is based on a model of fatigue loads of a two-turbine array. The particular novelty of the model is that fatigue loads are quantified using damage-equivalent load (DEL). Furthermore, the aerodynamic interaction of wind turbines through wakes and the downregulated operation of wind turbines is considered. In literature on wind farm control, the fatigue loads of wind turbines have typically been quantified using measures that are not necessarily measures of fatigue load \[28\], that is static forces \[17,18\] or the standard deviation of forces \[29\]. Static forces are only weakly related to fatigue loads. The standard deviation of a force can be used to compare the fatigue load, if the frequency spectrum of the different realizations of the force is the same. Among wind turbines in a wind farm this is however unlikely, since atmospheric and operational conditions are diverse. The use of DEL in the newly developed model in this thesis is considered suited, as it is a recognized measure employed to quantify fatigue loads of wind turbines. The developed model comprises two turbines and as a result, the effect of operational changes at the upstream turbine on the fatigue loads of the downstream turbine are considered. The approach is described in more details in section 4.3 of this thesis and in [J4]. The developed model is used in a model-predictive controller to estimate the impact of wind farm operation on fatigue loads. The design of the model-predictive controller allows for its future use as the above discussed optimization-based dispatch function.

1.1.2 Induction-driven Optimization in Nominal Operation

In nominal operation of wind farms, the objective is usually to maximize a farm’s total power production. The optimization approach is based on the hypothesis that some non-optimum operating condition of wind turbines increases total power production. As such, manually induced yaw misalignment at upstream turbines is investigated in numerical \[30,31\] and experimental \[32,33\] studies with the objective to shift the wake flow laterally and thereby increase the power of downstream turbines.

Another approach is the use of a positive offset of the blade pitch angle at the upstream turbine so that turbines downstream benefit from higher wind speeds in the weakened wake. This approach is termed induction-control in this thesis. An increase in total power production can be observed in simulations that are based on an actuator disc wind turbine model \[34,35\] or semi-empirical wake models \[36,38\]. Such models however simplify the aerodynamic interaction between wind turbines, in particular for
multiple wake cases. This results in an error between the model-estimated and the actual wind farm performance \[39\]. It is therefore of interest to investigate the approach in experiments and in higher fidelity simulation tools. In the wind tunnel studies in \[40,41\] an increase in total power is observed, whilst in the studies in \[42,43\] no increase is reported. The use of down-scaled models of wind turbines in wind tunnel tests results in a lower Reynolds number as compared to the full-scale, and as a result in differences of the turbine performance \[44\]. A wind farm control strategy developed in a wind tunnel will thus be different from the full scale. In the full-scale experiment in \[45\] an increase of the total power was observed. Mixed outcomes on the benefit of the approach are also reported in higher fidelity simulation studies. A CFD study based on Reynolds-averaged Navier-Stokes (RANS) reports an increase in total power \[46\]. A decrease in total power is reported in a study based on LES \[47\].

The experimental studies and high fidelity, numerical simulations were conducted in certain atmospheric conditions and turbine configurations, only. It is however unclear if the investigations were conducted in the most beneficial conditions. Therefore, in this work, a wide range of external conditions is analyzed, that is turbine spacing and atmospheric conditions comprising wind speed, wind direction, and turbulence intensity. Thereafter, the observed, potentially most beneficial condition is analyzed using the LES tool EllipSys3D. The LES provide a trustworthy insight into the effect of induction-control on the total power production. Furthermore, this work is – to the knowledge of the author – the first to give high fidelity evidence on the impact of induction-control on the fatigue loads of wind turbines in nominal operation.

### 1.2 Integration of Turbine Control Architecture

*This section \[1.2\] is based on publication \[C1\].*

When testing induction-control using a dynamic turbine model or a physical wind turbine, the offset in blade pitch angle is usually manually prescribed in the turbine controller. Thus, at present, the wind farm controller cannot effect an offset in pitch angle at wind turbines. In order to enable this, either the turbine control architecture could be modified or a set-point for the offset in blade pitch angle could be added to the controller inputs. The prior, that is changing the control approach, provides several advantages. First, the turbine remains a self-sustained unit with the robustness of operation ensured by the turbine control system. Second, the pitch angle might be simultaneously used for other turbine control procedures such as individual pitch control, and thus, setting the pitch angle externally could hamper the performance of these procedures. Third, the inputs to the turbine system remain in line with the International Electrotechnical Commission (IEC) norm \[48\]. Therefore, the modification of the turbine control architecture is being investigated in recent studies, typically with focus on the downregulation strategy.

The downregulation strategy defines the coordinated change of the blade pitch angle and rotor rotational speed used to adjust a turbine’s aerodynamic power. It thereby defines the effect of changing the power set-point on the pitch angle and rotor speed,
which in turn impacts the thrust of the turbine. The thrust influences the wake flow. As a result, the downregulation strategy can be used to influence the effect of the power set-point on wake flow. Consequently, the wind farm controller can coordinate the impact of wind turbines on wake flow using the power set-point. The employed downregulation strategy then defines the effect of changing the power set-point on wake flow. In the downregulation strategy of a standard turbine controller, the aerodynamic power is regulated by controlling the rotational speed of the rotor. When reaching the rated rotational speed, the aerodynamic power is controlled using the blade pitch angle. Thus, reducing the power set-point, for example, below rated speed results in an increase in rotor speed. However, the desired effect for induction-control would be an increase in pitch angle and thus reduction in thrust. Therefore, several, new approaches for downregulating a wind turbine are introduced in [38]. An approach is to control the turbine aerodynamic power using the blade pitch angle, both below and above the rated rotor speed. The approach therefore allows to influence the pitch angle using the power set-point, as desired for induction-control. Consequently, the wind farm controller can adjust the power set-point of wind turbines in order to thereby implicitly control the pitch angle and thrust of these wind turbines.

The approach is investigated in more detail in this thesis. The contributions to literature are the following. First, the approach is implemented in a dynamic turbine controller. Second, an insight into its working principles is given that allows for understanding the reduction in thrust as compared to a standard controller. The insight is given for both static and dynamic operation curves of a single turbine. Next, the developed controller is applied to a wind farm, which is operated in power control and induction-control mode. The wind farm simulations hence demonstrate an integrated solution for the control of both the individual wind turbines and the entire wind farm.

1.3 Spatial Variance in Measured Turbulence

This section (1.3) is based on publication [J2].

In areas in and related to wind farm control, turbulence measurements of the ABL flow are required. Common devices for the measurement of turbulence are sonic anemometers, cup anemometers and lidars. These devices provide an estimate of turbulence covering a confined volume of the ABL that is at the sensor location, or in the case of lidars, along the laser beam. Further, the measurements are sometimes performed distant from the desired location. Consequently, further processing can be required. In certain applications, turbulence measurements from multiple locations are aggregated to obtain statistical measures. In other applications, extrapolation is used to estimate turbulence at distant locations. However, the coherence of turbulence decreases with distance, particularly the larger the angle to the direction of wind flow [49]. Thus, with increasing distance the correlation of turbulence measurements decreases. The resulting spatial variance of turbulence introduces a random error when averaging and / or extrapolating distant turbulence measurements.

Such random error can be found in the control and monitoring of wind farms, and in
experimental research. In wind farm control, ambient turbulence intensity can be used as input to flow models. An approach is to average the turbulence measured at upstream turbines to estimate the ambient turbulence intensity. The averaging of turbulence introduces an error in the flow modelling due to the spatial variance of turbulence. This thesis discusses this error in more detail and proposes a possible solution. In wind farm monitoring, turbulence measurements are often used to classify wind turbine and/or wind farm performance. An example is the validation and monitoring of power curves of wind turbines according to turbulence intensity [50][51]. In power curve measurements, the location of turbulence measurements is usually upstream of the wind turbine.

When the measurement location is directly upstream, the random error due to the spatial variance of turbulence can be regarded as small assuming Taylor’s hypothesis of frozen turbulence. In case of an offset of the measurement location orthogonal to the direction of wind flow, a random error results, because of the spatial variance of turbulence. As for experimental research, turbulence measurements are used in the development of new sensors, flow models, improved wind turbine designs and more advanced wind farms. In [52], for example, the use of the rotor-effective wind speed is investigated for the measurement of turbulence intensity. The turbine-based measurements are compared to observations from an adjacent meteorological mast. As a result, the comparison is influenced by the spatial variance of turbulence.

In order to understand and quantify the impact of the spatial variance of turbulence, an analytical approach is developed for its calculation. Further, the spatial variance of turbulence is discussed for the above outlined application areas.

1.4 Research Objectives

In the scope of this thesis, a framework of an operational wind farm controller was developed comprising solutions for power control and induction-control. To enable power control according to multiple objectives of wind farm operation, a model-predictive optimization-based dispatch function was developed. The developed [DFP] provides computationally fast predictions of wind farm flow for use in power control. The multi-objective investigation of induction-control in [LES] showed reduced total power production and a beneficial decrease of fatigue loads of wind turbines.

The overall research objectives could be summarized as:

- Develop a wind farm controller framework to enable faster prototyping, design flexibility and a common environment for wind farm control, and create the capability to handle relevant modes of wind farm operation in numerical and experimental work.
- Enable multi-objective power control of wind farms to simultaneously provide accurate ancillary services and reduce fatigue loads of wind turbines.
- Develop a computationally fast, dynamic, control-oriented model of wind farm flow and operation for use in model-predictive control of wind farms.
• Investigate the impact of induction-control in wide range of external conditions and draw conclusion based on LES

• Develop integrated solutions for control of wind farms considering measurement inputs and turbine control aspects

1.5 Contributions

The scope of contributions of this thesis comprises the following additions:

• Development of integrated, modular DTU Wind Farm Controller framework comprising models of wind turbines, online measurement processing procedures, and a wind farm controller unit for power control and induction-control.

• Development of model-predictive optimization-based dispatch function for use in closed-loop feedback power controller.

• Development of DFP, a control-oriented, dynamic, linear model of wind farm flow and operation. Demonstration of suitability of DFP as linear version of successfully tested, comparable, nonlinear models.

• Application of DFP to model-predictive control of large-scale wind farms demonstrating improved tracking of reference for total power of wind farm.

• Development of multi-turbine model for fatigue loads of wind turbines.

• Integration of developed fatigue load model and DFP in model-predictive controller. Demonstration of significant reduction of sum fatigue loads of multi-turbine wind farm.

• Development of sPossPOW framework for modelling of stationary wind farm operation including a variety of models for the evolution of wind speed and turbulence intensity in wind farms.

• Development of offline and in-operational procedure for induction-control-based maximization of total wind farm power using sDWM or sPossPOW model, including algorithm to split optimization domain to reduce duration of optimization.

• Investigation of impact of induction-control in wide range of external conditions using analytic proof and model-based optimization including evaluation of most beneficial conditions in LES. Further, impact of induction-control on fatigue loads of wind turbines is quantified in LES.

• Development of turbine controller with novel downregulation strategy. Demonstration of developed turbine controller on single turbine and wind farm set-up. Investigations on wind farm include interaction with DTU Wind Farm Controller and different modes of wind farm operation
• Development of the first analytic solution for the quantification of the spatial variance of second-order moments of turbulence in the ABL. Demonstration of impact of spatial variance of second-order moments of turbulence on relevant applications in wind energy sector

1.6 Thesis Publications

The following publications are the result of this thesis and form the basis for the discussion in the ensuing chapters.

1.6.1 Journal Publications


1.6.2 Conference Publications


1.6.3 Division of Work between Authors

The division of work in the publications of this thesis was the following.

[J1] J. Kazda formulated the conceptual framework, planned the design of the study including scientific questions, carried out the developments and simulations and analysis and interpretation of results, and writing of article. N. A. Cutululis contributed with supervision, discussion and review of the work.

[J2] J. Kazda and J. Mann collaborated on the conceptual framework, planned the design of the study including scientific questions, carried out the developments and simulations and analysis and interpretation of results. J. Kazda undertook the writing of the article. J. Mann reviewed the manuscript.

[J3] J. Kazda formulated the conceptual framework, planned the design of the study including scientific questions, carried out the developments and simulations and analysis and interpretation of results, and writing of article. N. A. Cutululis contributed with supervision, discussion and review of the work.

[J4] J. Kazda formulated the conceptual framework, planned the design of the study including scientific questions, carried out the developments and simulations and analysis and interpretation of results, and writing of article. N. A. Cutululis contributed with supervision, discussion and review of the work. K. Merz and J. O. Tande contributed with the discussion and review of the work.

[C1] J. Kazda formulated the conceptual framework, planned the design of the study including scientific questions, carried out the simulations and analysis and interpretation of results, and writing of article. The development of turbine controllers was undertaken in collaboration with M. Mirzaei. M. Mirzaei further contributed with the discussion and review of the work. N. A. Cutululis contributed with supervision, discussion and review of the work.

[C2] J. Kazda formulated the conceptual framework, planned the design of the study including scientific questions, carried out the developments and simulations and analysis and interpretation of results, and writing of article. N. A. Cutululis contributed with supervision, discussion and review of the work.

[C3] J. Kazda formulated the conceptual framework, planned the design of the study including scientific questions, carried out the developments and simulations and analysis and interpretation of results, and writing of article. N. A. Cutululis contributed with supervision, discussion and review of the work.

[C4] J. Kazda formulated the conceptual framework, planned the design of the study including scientific questions, carried out the developments and simulations and
analysis and interpretation of results, and writing of article. N. A. Cutululis contributed with supervision, discussion and review of the work. G. Giebel and T. Göçmen contributed with the discussion and review of the work.

[C5] J. Kazda formulated the conceptual framework, planned the design of the study including scientific questions, carried out the developments and simulations and analysis and interpretation of results, and writing of article. N. A. Cutululis contributed with supervision, discussion and review of the work. M. Courtney, G. Giebel and T. Göçmen contributed with the discussion and review of the work.

1.7 Thesis Outline

This thesis comprises seven chapters, which are aligned to provide a logical flow to the reader. Nonetheless, the chapters can, to a large extent, be read independently, and thus, there is limited overlap with other parts of the thesis.

Chapter 1 A summary background of this thesis, and the research objectives and contributions are presented in the first chapter. The background is focused on the needs for further investigation and development in power control and induction-control of wind farms.

Chapter 2 In the second chapter, the developed DTU Wind Farm Controller framework is presented, in particular its benefits, structure, data storage and measurement processing procedures. The chapter furthermore describes how the framework connects the developments discussed in the ensuing chapters of this thesis.

Chapter 3 The first analytic solution for the quantification of the spatial variance of second-order moments of turbulence in the ABL is developed and successfully verified with simulations. The importance of the impact of the spatial variance of turbulence is demonstrated in relevant applications of the wind energy sector.

Chapter 4 Three developments for power control are described in chapter four. First, the DFP is presented and demonstrated in relevant applications including a large-scale wind farm. Second, the developed model-predictive optimization-based dispatch function for use in the framework’s closed-loop power controller is introduced and successfully applied to a large-scale wind farm. Third, the developed fatigue load model is used in model-predictive control of a wind farm to reduce sum fatigue loads of wind turbines.

Chapter 5 The potential power gain obtained from the use of induction-control is investigated in a wide range of external conditions using analytic proof and model-based optimization. Conclusions are drawn with respect to power production and fatigue loads using LES.

Chapter 6 The architecture of turbine control is investigated with the objective to reduce wind turbine thrust and as a result adverse wake effects in wind farms. The newly developed turbine controller is successfully tested in interaction with the
Wind Farm Controller in power control and induction-control of a wind farm in dynamic simulations.

Chapter 7  The chapter presents the summary of the results of this thesis and final concluding remarks. The chapter is closed with suggestions for potential future work.
Chapter 2

Wind Farm Controller Framework

This chapter presents the [DTU] Wind Farm Controller framework and outlines its individual components. The framework was developed in this thesis due to its intrinsic benefits for [DTU] Wind Energy. Its major advantages are faster prototyping, design flexibility and a common environment for the development of wind farm control. These are facilitated by the modular program architecture of the framework in all relevant areas of its structure. The framework consists of five high-level units, that is a measurement processing unit, two wind farm controller units, a unit of data and models on the wind turbine cluster, and a unit on wind farm operation models. The unit on data and models of the wind turbine cluster comprises turbine-specific data storage and models of the wind turbines in the wind farm. The measurement processing unit performs pre-processing of raw measurement data from wind turbines and provides the post-processed data to the wind farm control units upon demand. The units on wind farm control and operation models are outlined in this chapter and discussed in detail in the ensuing chapters of this thesis.

2.1 Introduction

When commencing the PhD studies there was yet no framework for wind farm control at [DTU] Wind Energy. Due to the intrinsic benefits of such framework, the [DTU] Wind Farm Controller framework [C5] was developed in this thesis.

The framework provides several advantages and benefits. The most important ones are fast prototyping, design flexibility and a common environment for the development of wind farm control. The former two are enabled by the modular program architecture on all, relevant levels of the framework’s structure. Thereby, reusability of framework modules is possible, which reduces the time required for prototyping. As such, when, for example, creating a new control-oriented model of wind farm operation, the development can reuse procedures for processing measurement data and models of wake flow. Further, the newly developed model can easily be tested in existing model-based wind farm controllers. The modular structure of the framework also enables design
flexibility. As such, when the framework is applied to a particular environment, the
modules, that are best suited for it, can be used with no additional effort in implementa-
tion. Further, the performance of same-purpose modules can be compared with each
other quickly. Next, the **DTU** Wind Farm Controller framework also creates a com-
mon environment for the development of tools for wind farm control. As a result, it
eases collaboration on and testing of wind farm control. With regards to testing, the
framework provides a standard interface for the investigation of new wind farm con-
trol methods in simulation and real wind farms. The applicability to real wind farms is
achieved by using the same inputs and outputs as an industry wind farm controller, and
by the capability to handle the common operation modes of wind farms.

### 2.2 Framework Structure

The **DTU** Wind Farm Controller is a framework for an operational wind farm controller
that comprises a variety of options for wind farm control, models of wind farm oper-
aton and approaches for processing measurement inputs online. Figure 2-1 shows the
high-level structure of the **DTU** Wind Farm Controller framework and its interaction
with the controlled system, that is the wind turbines of the wind farm.

![Diagram of DTU Wind Farm Controller framework](image)

**Figure 2-1:** High level structure of **DTU** Wind Farm Controller and its interaction with
wind turbines in wind farm.

Input to the framework are selected measurements from the wind turbines. Output
from the framework are the set-points to the wind turbines. The framework’s high level
components are a measurement processing unit, the unit on data and models of the wind
turbine cluster, models of wind farm operation, and two wind farm controller units. In
the measurement processing unit, the measurements of the wind turbines are processed
and provided to the wind farm controller units. The unit on data and models of the
wind turbine cluster provides storage of data and wind farm characteristics. The unit on data and models of the wind turbine cluster and the unit on measurement processing are introduced in more detail in the subsequent sections of this chapter. The wind farm controller units are outlined in the following and discussed in more detail in the ensuing chapters of the thesis. The objectives of the two units are, for one unit, the maximization of wind farm power, and, for the other, the tracking of the reference for the total power of the wind farm. Wind farm control with the latter objective is termed power control in this thesis. Output of the wind farm control units are the set-points to the wind turbines.

**Unit: Power Maximizing Controller**

The unit of the power maximizing controller comprises a variety of options to perform wind farm control with the objective to maximize the total power of the wind farm. The algorithms developed for power maximizing operation are presented in detail in chapter 5 and outlined in the following. The developed algorithms comprise model-based and model-free approaches.

The model-based controllers can derive operation strategies using in-operational optimization or offline optimization. The wind farm operation models employed for optimization are S-DWM and SPosPOW. With regards to model-free algorithms, a controller based on Bayesian-optimization is part of the framework, yet was developed outside of this thesis. More details on the approach can be found in [53]. The framework further contains a wind farm controller with the objective to maximize each individual turbine’s power. This is the present standard approach of power maximizing wind farm control. The controller is mainly used as reference for the assessment of new controller developments. An overview of the algorithms and models of the power maximizing controller unit is shown in section 5.2.1 in Figure 5-1 and Figure 5-4.

**Unit: Power Control**

The unit on power control comprises a variety of options to perform wind farm control with the objective to track the reference for the total power of the wind farm. The algorithms developed for this unit are presented in chapter 4 and outlined in the following. In section 4.2 a feedback, PI-controller is introduced and in section 4.3 a model predictive controller (MPC) is presented.

The novelty of the feedback controller is the use of model-based optimization to determine the distribution of the requested total power to the wind turbines in the wind farm. The model-predictive controller was developed with the objective to mitigate wind turbine fatigue loads during power control of wind farms. The developed power controllers use two, newly developed, control-oriented models, the DFP and a statistical fatigue load model. The DFP is a fast, control-oriented, dynamic, linear model of wind farm flow and operation, which is presented in more detail in section 4.1. The statistical load model provides an estimate of the effect of downregulated operation on the fatigue loads of a two-turbine array. As discussed in section 4.3.3, such estimate is beneficial in power control.
2.3 Data and Models of Wind Turbine Cluster

The unit on Data and Models of the Wind Turbine Cluster is a data and modelling structure that comprises turbine-specific data storage and models of the wind turbines of the wind farm. Data is stored from the measurement processing unit and the wind farm control units. As such, the pre-processed measurement data is stored intermediately for later post-processing and use in the wind farm control units. Similarly, the wind farm control units store optimization results for later use.

The models of the unit describe the turbines’ characteristics and layout. The approach of modelling is modular, as shown in Figure 2-2. The wind turbine cluster is composed of individual turbine modules, one for each turbine, and thereby allows to characterize each turbine differently. Each turbine module consists of multiple sub-modules for different areas of turbine characteristics. That is a model of turbine operation, the rotor aerodynamics, the power curve, the sensors, the turbine location, and the wind conditions, which are described in more detail, in the following.

![Modular structure for data and modelling of wind turbine cluster. Structure consists of individual turbine modules with each turbine module comprising data storage and models of turbine characteristics.](image)

Figure 2-2: Modular structure for data and modelling of wind turbine cluster. Structure consists of individual turbine modules with each turbine module comprising data storage and models of turbine characteristics.

**Module: Wind Conditions**

The wind conditions module comprises sensor models and respective data storage of the measurement of the conditions of wind flow in the proximity of the wind turbine.
The available sensor models are wind vane, cup anemometer, sonic anemometer, and nacelle direction sensor. The sensors included in the module depend on which sensors are present on the wind turbine.

**Module: Location**

The module of turbine location stores the geographic location of the wind turbine. That is easting and northing in **Universal Transverse Mercator (UTM)** coordinates and height above sea level. Further, the module can store the hub height of the wind turbine.

**Module: Power Curve**

The Power Curve module comprises the characteristics of a turbine’s nominal power curve. That is the turbine’s nominal power as function of wind speed, and in the future, as function of turbulence intensity. The module also contains information about cut-in, rated and cut-out wind speed. The power curve can be specified explicitly using an input file or in an implicit manner by specifying cut-in, rated, and cut-out wind speed, and the rated power of the wind turbine, which results in the automatic creation of a generic power curve.

**Module: Sensor Models**

The purpose of the sensor models is to allow for sensor-specific measurement data processing. As such, processing methods tailored to the characteristics of a sensor can be used to pre-process raw measurement data. Such processing methods can be, but are not limited to, filter functions, value bounds, and validity checks. More details on the use of these methods is described in section **2.4**. The pre-processed data is intermediately stored in a circular buffer of the sensor model for later use in the post-processing. The present use of sensor models in the **DTU** Wind Farm Controller framework is shown in Table **2.1**.

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Measurements used in</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generator power</td>
<td>wind farm models, wind farm controllers,</td>
</tr>
<tr>
<td></td>
<td>rotor effective wind speed method</td>
</tr>
<tr>
<td>Nacelle direction</td>
<td>wind farm models, wind farm controllers</td>
</tr>
<tr>
<td>Cup anemometer</td>
<td>wind farm models</td>
</tr>
<tr>
<td>Sonic anemometer</td>
<td>wind farm models</td>
</tr>
<tr>
<td>Rotor rotational speed</td>
<td>wind farm models, rotor effective wind speed method</td>
</tr>
<tr>
<td>Blade pitch angle</td>
<td>wind farm models, rotor effective wind speed method</td>
</tr>
<tr>
<td>Wind vane</td>
<td>wind farm models</td>
</tr>
</tbody>
</table>

Table 2.1: Use of sensor measurements in **DTU** Wind Farm Controller framework.
Module: Operation Model

The Operation Model relates characteristic variables of stationary turbine operation with each other, considering the characteristics of the turbine and its controller. The variables are the electrical power output, the power coefficient, the thrust coefficient, the tip-speed ratio and the blade pitch angle. The thrust coefficient is calculated as a function of the tip-speed ratio and the blade pitch angle. The power coefficient $c_P$ is related to the power output $P_{el}$ as

$$c_P = \frac{P_{el}}{\frac{1}{2}\rho A u^3 \mu}$$

(2.1)

where $\rho$ is the air density, $A$ the rotor area, $u$ the rotor effective wind speed, and $\mu$ the mechanical to electrical conversion efficiency from turbine rotor to turbine generator. The power coefficient is also related to the tip-speed ratio and blade pitch angle using the downregulation strategy of the turbine controller.

The operation model comprises three, commonly used downregulation strategies, that is the present standard approach for turbine control [54], the constant tip-speed ratio method [38], and the constant torque-speed approach. Other downregulation strategies can be found in [38]. Since the constant torque-speed method is - to the author’s knowledge - not described in literature, it is outlined in the following. The generator torque is set using the torque-speed curve as described in [54] both in nominal and in downregulated turbine operation. The turbine’s aerodynamic power is controlled using the blade pitch angle. In nominal operation the objective is to maximize the aerodynamic power, and hence the pitch angle is set to its nominal value. In downregulated operation, the blade pitch angle is controlled with the objective to minimize the deviation between the power set-point and power output of the wind turbine.

Further details on downregulation strategies and its impact on the operation of the wind turbine and wind farm are discussed in chapter 6 of this thesis.

Module: Rotor Aerodynamic Model

The rotor aerodynamic model describes the turbine’s power coefficient and thrust coefficient and several, further, control-related characteristics of the rotor. The power coefficient and thrust coefficient is obtained as a function of the rotor’s blade pitch angle and tip-speed ratio. The relation is quantified using look-up tables or empirical functions. The other control-related characteristics stored in the rotor aerodynamic model are rotor diameter, the rated rotational speed of the rotor and the rotor inertia.
2.4 Measurement Processing

In the measurement processing unit, the measurements of the wind turbines are processed for further use by the wind farm controller units. The handling of measurement data is structured into two steps: pre-processing and post-processing, as shown in Figure 2-3.

In the pre-processing, data quality checks are performed and signals are processed further before storage. The data quality checks test the validity of the measurement by evaluating if the measurement input is numeric and if the value is within a valid range. Sensor specific processing procedures can, for example, employ filters to handle noise and other distortions in the measurements. The pre-processed data is stored in a buffer storage for later use in post-processing procedures. Post-processing procedures are then used in the control modules of the DTU Wind Farm Controller framework in order to calculate quantities of interest. Such can be the rotor effective wind speed and statistical measures of the measurements such as time-average or standard deviation over a specific time horizon.

![Figure 2-3: Structure of measurement processing and measurement data storage used in DTU Wind Farm Controller.](image)

For flows models of wind farm controllers there is typically three, important wind condition inputs, that is wind speed, wind direction and turbulence intensity at wind turbines. In the following, approaches for the improved measurement of these are discussed, which are part of the DTU Wind Farm Controller framework. In this chapter the measurement of wind speed and wind direction is discussed, and in the ensuing
chapter, the measurement of turbulence intensity is investigated.

2.4.1 Rotor-Effective Wind Speed

The rotor-effective wind speed method is useful, since nacelle-based wind speed measurements are usually affected by the aerodynamic influence of the wind turbine rotor. This is because wind speed anemometry is located on the turbine’s nacelle and thus experiences the turbulent, near-wake flow behind the wind turbine. In the DTU Wind Farm Controller framework, the dynamic rotor-effective wind speed algorithm is implemented with the following calculation procedure. Given the conservation of power, the aerodynamic power $P_{aero}$ of a wind turbine can be related to the electrical power $P_e$ as

$$J\omega \dot{\omega} = P_{aero}(\lambda) - \frac{1}{\eta} P_e$$  \hspace{1cm} (2.2)

where $J$ is the inertia of the wind turbine rotor and shaft equivalent for the rotor rotational speed, $\omega$ the rotor rotational speed, $\dot{\omega}$ the time-derivative of the rotor rotational speed, and $\eta$ is the mechanical to electrical conversion efficiency of the wind turbine. $\lambda$ is the TSR of the rotor which is defined in this work as

$$\lambda = \frac{\omega R}{u}$$  \hspace{1cm} (2.3)

where $R$ is the rotor radius and $u$ the rotor effective wind speed. The aerodynamic power of the wind turbine can be calculated as

$$P_{aero}(\lambda) = \frac{1}{2} \rho A \left(\frac{\omega R}{\lambda}\right)^3 c_P(\lambda, \beta)$$  \hspace{1cm} (2.4)

where $\rho$ is the air density, $A$ the swept area of the rotor, $c_P$ the power coefficient of the wind turbine, and $\beta$ the collective blade pitch angle. The rotor effective wind speed $u$ is obtained from Eq. 2.2 using a non-linear equation solver. Since there is typically two feasible solutions, the developed algorithm automatically constrains the solver in order to yield the correct solution. The constraints are set using the downregulation strategy of the wind turbine, which allows to determine a realistic range of TSR and blade pitch angle.
Figure 2-4: Benefit of dynamic rotor effective wind speed method in accuracy of wind speed estimation. (a) Comparison of dynamic and static version of rotor effective wind speed method. Simulation is conducted on NREL 5 MW turbine model simulated in SWF (b) turbine power output and (c) rotor rotational speed.
The benefit of using the dynamic version of the rotor effective wind speed method as compared to the static version is discussed in the following. In the static version, the aerodynamic power is related to the electrical power output as

\[ 0 = P_{aero}(\lambda) - \frac{1}{\eta} P_e \]  

(2.5)

The difference to the dynamic version is that the dynamic version considers the rate of change in kinetic energy in the rotor. In Figure 2-4, the performance of these two versions is compared in dynamic simulations. The simulations are conducted in SWF [55] on the NREL 5 MW turbine model [56]. More details on the simulation environment can be found in Chapter 4 of this thesis. To ease understanding of the comparison, the true wind speed upstream of the wind turbine is 8 m/s and constant throughout the simulation. The power output of the wind turbine is changed step-wise as shown in Figure 2-4.b. The change in power output affects the solution of the rotor effective wind speed method, as can be seen in Eq. 2.2 and Eq. 2.5. In Figure 2-4.a it can be observed that the \( t_{90} \) rise time in the dynamic version is 10-times faster than in the static version. The \( t_{90} \) time is defined as the duration after which a variable reaches 90% of the change in value to its new equilibrium. The faster rise time of the dynamic rotor effective wind speed method is because it accounts for the change of kinetic energy in the rotor.

### 2.4.2 Wind Direction Offset

In wind farm control, the wind direction at wind turbines is usually determined from measurements of the nacelle direction or wind vane sensor. The accuracy of these measurements is of importance, since wake effects on downstream turbines are sensitive to changes in wind direction. At times, these sensors can give biased measurements.

In order to correct for the bias, the power deficit-based approach [57] is used to determine the magnitude of the bias at upstream turbines. The procedure of the approach is the following. To correct the bias of wind direction measurements of an upstream turbine, an adjacent downstream turbine is selected. To ensure the proper functioning of the method the upstream turbine needs affect the downstream wind turbine by its wake. Such is the case if the upstream turbine is operating at a high thrust coefficient and the spacing of the turbines is small, approximately less than 10D. An example of such scenario is shown in Figure 2-5b. Next, the ratio of the power output of the downstream turbine to the power output of the upstream turbine is categorized according to the direction of the nacelle at the upstream turbine, as shown in Figure 2-5b. As can be seen in Figure 2-5a the nacelle direction of 0° does not coincide with the actual north due to the bias in the sensor measurement. As a result, the maximum power deficit at the downstream turbine is observed at an offset of 9°, as shown in Figure 2-5b. To detect the offset from the noisy measurements, a normal distribution is fitted to the measurement data. The mean of the normal distribution provides the estimate for the bias in the nacelle direction measurements.
2.5 Automatic Controller Switching

This section describes the implementation of the automatic switching between the two wind farm controller units, that is the unit for power maximizing control and the unit for power control. The choice of the activated wind farm controller is made according to the present mode of wind farm operation. A change in the mode results in an automatic switching between the two controller units. In the present implementation, the mode of wind farm operation is obtained from the value of the reference signal for the total power. A value below the rated total power of the wind farm results in power reference following operation. Otherwise, the wind farm is operating in power maximizing operation.
Chapter 3

Mitigating Impact of Spatial Variance in Measured Turbulence

The first analytical solution for the quantification of the spatial variance of second-order moment of correlated wind speeds was developed in this work. The approach is successfully verified using simulation and field data. The impact of the spatial variance on three, selected applications of the wind energy sector is then investigated including mitigation measures. First, the variance of the second-order moment between front-row wind turbines of Lillgrund wind farm is investigated. The variance ranges between 25% and 48% for turbulence intensities ranging from 7% to 10%. It is thus suggested to use the second-order moment measured at each individual turbine as input to flow models of wind farm controllers in order to mitigate random error. Second, the impact of the spatial variance of the measured second-order moment on the verification of wind turbine performance is investigated. Misalignment between the mean wind direction and the line connecting the meteorological mast and wind turbine results in a random error in the observed second-order moment of wind speed. Such random error brings uncertainty in turbulence intensity-based classification of the fatigue loads and power output of the wind turbine. To mitigate the random error it is suggested to either filter the measured data for low angles of misalignment, or to quantify wind turbine performance using the ensemble averaged measurements of the same wind conditions. Third, the verification of sensors in wind farms can involve distant reference measurements. In case of a misalignment between the wind direction and the line connecting sensor and reference, a random error will hamper the comparison of second-order moments measured at distant locations. The suggested mitigation measures are the same as for the verification of turbine performance.

Chapter 3 is based on publication [J2].

3.1 Introduction

Many areas of the wind energy sector require measurements of the wind turbulence in the ABL. A common measure to quantify turbulence is turbulence intensity. It is defined according to the IEC norm [58] as the ratio of the square root of the second-
order moment of axial wind speed to the mean, axial wind speed obtained for the same
10-min period. Common devices for the measurement of the second-order moment of
wind speed are sonic anemometers, cup anemometers and lidars. These devices provide
an estimate of the second-order moment covering a confined volume of the ABL that is at the sensor location, or in the case of lidars, along the laser beam. However, these measurements are, at times, performed distant from the desired location. Consequently, further processing can be required. In some applications, measurements from multiple locations are aggregated to obtain statistical measures. In other applications, extrapolation is used to estimate the second-order moment of turbulent wind speed at distant locations. However, second-order moments of wind speed measured at distant locations can be different from each other. This is because the coherence of turbulence decreases with distance, particularly the larger the angle to the direction of wind flow. The resulting spatial variance of the second-order moment of wind speed introduces a random error when averaging and / or extrapolating distant turbulence measurements.

Such random error can be found in a variety of areas in the wind energy sector. This work focuses on three areas, that is wind farm control, the verification of wind turbine performance, and sensor verification. In wind farm control, ambient turbulence intensity is often used as input to flow models. Measurements of ambient turbulence intensity are usually obtained from upstream turbines of the wind farm. Because of the distance between the wind turbines, the measured second-order moment of wind speed varies between the wind turbines. This thesis therefore investigates the magnitude of the variation. The results are used to discuss approaches for the use of turbulence intensity measured at upstream turbines in flow models.

In the verification of wind turbines, turbulence intensity measurements are used to classify turbine performance. This is because turbulence intensity in the flow approaching a wind turbine influences the fatigue loads and power output of the wind turbine. Turbulence intensity is usually measured at meteorological masts adjacent to the wind turbine. As a result of the distance between mast and wind turbine, the spatial variance of the second-order moment can impact the accuracy of the measured turbulence intensity. Uncertainty in the measured turbulence intensity propagates in to the uncertainty of measured power and fatigue loads of the wind turbine. When the mast location is directly upstream, the random error due to the spatial variance of turbulence can be regarded as small assuming Taylor’s hypothesis of frozen turbulence. In case of an offset of the mast location orthogonal to the direction of wind flow, a random error results, because of the spatial variance of turbulence. The magnitude of the impact and approaches for its mitigation are therefore investigated in this thesis. Finally, the spatial variance can also impact the verification of sensors in wind farms. For example in the use of the rotor-effective wind speed is investigated for the measurement of turbulence intensity. The turbine-based measurements are compared to observations from an adjacent meteorological mast. As a result, the comparison is influenced by the spatial variance of the second-order moment of wind speed.

In order to understand and quantify the impact of the spatial variance of turbulence, an analytical approach is developed for its calculation in this thesis. The further contribution of this work is the investigation of the impact of the spatial variance of the second-order moment of wind speed on the three above outlined areas. Finally, ap-
proaches for the mitigation of the impact of the spatial variance are discussed.

The remainder of this chapter is structured as follows. Next, the developed approach for the quantification of the spatial variance of the second-order moment of wind speed is detailed. Thereafter, the random error due to spatially distant measurements of second-order moments is discussed for three, selected applications. The chapter is concluded with a summary of the key findings.

3.2 Spatial Variance of Second-order Moment

The expected, spatial variance of the second-order moment of wind speed measured over a time period $T$ at two, spatially-separated points $a$ and $b$ can be calculated as shown in the following. The expected, spatial variance of the second-order moment of line-of-sight (LOS) wind speed $\delta \mu^2_{2, L, a-b}$ is defined as

$$\delta \mu^2_{2, L, a-b}(T) = \langle [\mu_{2, L, a}(T) - \mu_{2, L, b}(T)]^2 \rangle \quad (3.1)$$

where $\mu_{2, L, a}(T)$ and $\mu_{2, L, b}(T)$ are second-order moments measured at the points $\vec{a} = (a_x, a_y, a_z)$ and $\vec{b} = (b_x, b_y, b_z)$ in the ABL. The LOS direction of measurement is assumed to be the same at the points $\vec{a}$ and $\vec{b}$. $x$, $y$, and $z$ are the coordinates of the Cartesian coordinate system. $x$ is set to the mean direction of wind flow, $y$ is the horizontal coordinate orthogonal to $x$, and $z$ the vertical coordinate. The measured second-order moment of LOS wind speed $\mu_{2, L}(T)$ is defined as

$$\mu_{2, L}(T) = \frac{1}{T} \int_{-T/2}^{T/2} (u_L(t) - \bar{u}_L)^2 dt \quad (3.2)$$

where $u_L(t)$ is the LOS wind speed and $\bar{u}_L$ is the LOS wind speed averaged over the time interval $[-T/2, T/2]$. The LOS wind speed is defined as

$$u_L = \vec{n}_L \cdot \vec{u} \quad (3.3)$$

where $\vec{n}_L = (n_{L,x}, n_{L,y}, n_{L,z})$ is the unit-directional vector in the direction of LOS and $\vec{u} = (u, v, w)$ is the wind velocity.

Assuming a homogeneous, turbulent field, the expected, spatial variance of the second-order moment (Eq. 3.1) can be reformulated as

$$\delta \mu^2_{2, L, a-b}(T) = 2[\langle \mu_{2, L}(T)^2 \rangle - \langle \mu_{2, L, a}(T) \mu_{2, L, b}(T) \rangle] \quad (3.4)$$

Next, assuming that the mean wind speed $\bar{u}_L$ is zero and that $u_L(t)$ can be represented
by a Gaussian process, Isserlis’ Theorem [64, 65] is applied to Eq. 3.4 resulting in

\[
\delta \mu_{2,L,a-b}^2(T) = \frac{4}{T^2} \left[ \iint_{-\frac{T}{2}}^{\frac{T}{2}} \langle u_L(t)u_L(t') \rangle^2 dt dt' \right. \\
\left. - \iint_{-\frac{T}{2}}^{\frac{T}{2}} \langle u_{L,a}(t)u_{L,b}(t') \rangle^2 dt dt' \right] (3.5)
\]

\[
\delta \mu_{2,L,a-b}^2(T) = \frac{4}{T^2} \left[ \iint_{-\frac{T}{2}}^{\frac{T}{2}} (\vec{n}_L^T R(\vec{0}, t-t')\vec{n}_L)^2 dt dt' - \\
\iint_{-\frac{T}{2}}^{\frac{T}{2}} (\vec{n}_L^T R(\vec{a}-\vec{b}, t-t')\vec{n}_L)^2 dt dt' \right] (3.6)
\]

where \( R(\vec{r}, \tau) \) is the two-point correlation tensor of wind velocity, \( \vec{r} \) the vector connecting the two points, and \( \tau \) the time delay. The integral of the correlation tensor can be obtained from the infinite volume integral of the spectral tensor \( \Phi(\vec{k}) \) as

\[
\iint_{-\frac{T}{2}}^{\frac{T}{2}} (\vec{n}_L^T R(\vec{a}-\vec{b}, t-t')\vec{n}_L)^2 dt dt' = \\
\iint_{-\frac{T}{2}}^{\frac{T}{2}} \left[ \iint_{-\infty}^{\infty} \vec{n}_L^T \Phi(\vec{k}) \vec{n}_L \\
\exp \left( i\vec{k}(\vec{a}-\vec{b} + (U_0 0 (t-t'))) \right) dk_1 dk_2 dk_3 \right]^2 dt dt' (3.7)
\]

The time delay \( \tau \) is introduced using Taylor’s hypothesis of frozen turbulence as the spatial separation \( \Delta x = U(t-t') \) in axial flow direction. \( U \) is the mean wind speed in axial flow direction when averaging over the time interval \([-T/2, T/2]\). The spectral tensor \( \Phi(\vec{k}) \) can be obtained using the model of Mann [66]. \( \vec{k} \) is the three-dimensional wave number vector. The three dimensional, infinite integral over the wave number space is denoted as \( \iint d\vec{k} = \iint_{-\infty}^{\infty} dk_1 dk_2 dk_3 \) in the following. Expanding above equation and solving the time integral yields
\[
\int \int \frac{T}{2} (\vec{n}_L^T \mathbf{R} (\vec{a} - \vec{b}, t - t') \vec{n}_L)^2 dt dt' = \\
\int \int (\vec{n}_L^T \Phi (\vec{k}) \vec{n}_L) (\vec{n}_L^T \Phi (\vec{k}') \vec{n}_L) \exp(i(\vec{k} + \vec{k}')(\vec{a} - \vec{b})) \sin^2 \left( \frac{(k_1 + k_1')TU}{2} \right) T^2 d\vec{k} d\vec{k}' \quad (3.8)
\]

The derived equation (3.8) is used in the original problem (Eq. 3.5) yielding an analytical solution for the spatial variance of the second-order moment.

\[
\delta \mu_{2,L,a-b}^2 (T) = 4 \int \int (\vec{n}_L^T \Phi (\vec{k}) \vec{n}_L) (\vec{n}_L^T \Phi (\vec{k}') \vec{n}_L) \left[ 1 - \cos ((\vec{k} + \vec{k}')(\vec{a} - \vec{b})) \right] \sin^2 \left( \frac{(k_1 + k_1')TU}{2} \right) d\vec{k} d\vec{k}' \quad (3.9)
\]

In the following, the normalized spatial variance of the second-order moment \( \delta M_{2,L,a-b} \) is defined as

\[
\delta M_{2,L,a-b} = \sqrt{\frac{\delta \mu_{2,L,a-b}^2}{\langle \mu_{2,L}(T) \rangle}}
\]

\[
= \sqrt{4 \int \int (\vec{n}_L^T \Phi (\vec{k}) \vec{n}_L) (\vec{n}_L^T \Phi (\vec{k}') \vec{n}_L) \left[ 1 - \cos ((\vec{k} + \vec{k}')(\vec{a} - \vec{b})) \right] \sin^2 \left( \frac{(k_1 + k_1')TU}{2} \right) d\vec{k} d\vec{k}'}
\]

\[
= \frac{\int \int \int \int_{-\infty}^{\infty} (\vec{n}_L^T \Phi (\vec{k}) \vec{n}_L) \left[ 1 - \sin^2 \left( \frac{k_1 TU}{2} \right) \right] d\vec{k}}{(3.10)}
\]

The normalization is performed using the ensemble second-order moment of LOS wind speed \( \langle \mu_{2,L}(T) \rangle \).

### 3.3 Results & Discussion

The developed analytical solution is verified in the following. Thereafter, the mitigation of the impact of the spatial variance of the second-order moment of wind speed is investigated.
3.3.1 Verification of Analytical Solution

The derived analytical solution for the calculation of the spatial variance of the second-order moment (Eq. [3.10]) is verified in the following using a simulated, turbulent wind field.

Simulation Set-up

The turbulent wind field is created using the simulation approach of the Mann model [67]. The simulation domain has the dimensions of 5000m x 600m x 600m in the x, y, and z direction, respectively. The geometric characteristics of the simulation domain and grid are summarized in Table 3.1.

<table>
<thead>
<tr>
<th>Direction</th>
<th>x</th>
<th>y</th>
<th>z</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dimension</td>
<td>5000m</td>
<td>600m</td>
<td>600m</td>
</tr>
<tr>
<td>Grid points</td>
<td>1024</td>
<td>128</td>
<td>128</td>
</tr>
<tr>
<td>Grid spacing</td>
<td>4.88m</td>
<td>4.69m</td>
<td>4.69m</td>
</tr>
</tbody>
</table>

Table 3.1: Key characteristics of domain and grid of simulated wind field.

Atmospheric Conditions

In both the simulations and for the analytical solution, the ABL is set to be characterized by neutral stability. Thus, according to [68] the spectral parameters of the Mann model are set to $\alpha = 1$, $L = 50$ m, $\Gamma = 3.2$. The mean wind speed in the mean wind direction is 8m/s. The duration of averaging $T$ is set to 10min, as it is used for turbulence measurements in the IEC norm [58].

Comparison with Simulation

To verify the analytic solution, it was compared with the spatial variance of the second-order moment observed in the simulated wind field. The comparison was conducted for the second-order moment of the axial wind speed $u$ for spatial separation of measurement points $a$ and $b$ in the $y$ and $z$ direction. Figure 3-1 shows the results of the comparison. The spatial variance of second-order moment was normalized by the expected second-order moment, as described in equation [3.10]. The analytic solution was evaluated using adaptive, multidimensional, numerical integration [69, 70].

The overall agreement between the analytic solution and the simulation results demonstrates the validity of the analytic solution. The same trend can be observed in the results of analytic solution and of the simulation. The agreement is better for close separation distances of up to 50m. Here, the mean difference is only 2.6% and 0.55% for separation in $y$ and $z$ direction, respectively. Further, in both simulations and the analytic solution, with increasing spatial distance between the measurement points, the
Figure 3-1: Simulation-based validation of analytic calculation of spatial variance of second-order moment of ABL wind flow. Comparison is conducted for second-order moment of axial wind speed $u$ for spatial separation of two points in the cross-axial and vertical direction. Source: [J2]

difference in the second-order moment measured at each of the points increases, as expected. This is due to a decreasing coherence of wind turbulence with larger separation distance [49]. At large separation distances both the analytic solution and the simulation results converge to an asymptotic value. The simulation results converge to 0.37 and 0.35 for separation in $y$ and $z$ direction, respectively. The results obtained with the analytic solution converge to the same value of 0.34. The asymptotic behaviour can be understood from the analytic solution, particularly from the behaviour of the term $[1 - \cos((\vec{k} + \vec{k}')(\vec{a} - \vec{b}))]$ in equation (3.10). For large distances between the measurement points $\vec{a}$ and $\vec{b}$, the fluctuation of the cosine term is much faster than the change of the remainder of the integrand. Thus, the integral over a period of the cosine is well approximated by the remainder of the integrand. Consequently, the cosine term can be neglected for large separation distances and, the spatial variance of the second order moment converges to an asymptote. Furthermore, neglecting the cosine term for large separation distances results in the asymptote to be the same for separation in the $y$ direction and the $z$ direction. This can be observed in Figure 3-1 at a separation of 300m.

It can further be observed that the simulation results are generally larger than the results of the analytic solution. This can be due to lower ensemble variance of axial wind speed $\langle u^2 \rangle$ in the simulations. Turbulent eddies smaller than the grid spacing cannot be captured in the simulation, and as a result, the observed variance of wind speed is lower.

In addition to the effect of the separation distance, the results show that the spatial variance of axially-measured turbulence increases faster in the cross-axial direction $y$
than in the vertical direction $z$. This is the result of stronger spectral-coherence of turbulence in $z$-direction than in $y$-direction.

### 3.3.2 Mitigation of Impact in Applications

The spatial variance of the second-order moment of wind speed impacts a variety of applications in the wind energy sector. For the present work, three areas were selected for more detailed discussion, that is wind farm control, the verification of wind turbine performance, and sensor verification.

#### Wind Farm Control

In wind farm control, measurements of turbulence intensity are often used as input to flow models \cite{25, 59, 60}. As turbulence intensity is defined as the ratio of the second-order moment of axial wind speed $u$ and the mean wind speed, measurements of the second-order moment of wind speed are required. A commonly used measure is the ambient turbulence intensity in the free flow. An approach to obtain the ambient turbulence intensity is to average the measured turbulence intensity at all upstream turbines. It is shown in the following that such approach is likely to introduce a random error into the flow modelling. This is because of the variance of the measured second-order moment of wind speed between the turbines.

To show this, the variance of the second-order moment was investigated on the westerly, front row of turbines of Lillgrund wind farm, as shown in Figure 3-2. Lillgrund wind farm is located offshore, south-east of Copenhagen, Denmark. The front row comprises five wind turbines spaced by approximately five rotor diameters, that is 450m.

![Figure 3-2: Front row of Lillgrund wind farm seen from west. Variance of second-order moment of nacelle wind speed between wind turbines is investigated with turbine no. D08 for reference. Source: [J2]](image)

Given a wind direction from west, that is $270^\circ$, the spacing of wind turbines orthogonal to the average direction of wind flow is more than 400m. Hence, the turbulence mea-
urements at wind turbines in the front row are separated with at least that distance. As can be seen in Figure 3.1, in such separation distances the normalized variance of the second-order moment of axial wind speed is 34% according to the developed analytic solution. It is shown in the following that a similar variance can also be observed in the westerly, front row of Lillgrund wind farm.

The investigation used data from more than 7 years of measurements. The ensemble average of the second-order moment of wind speed at the turbines was obtained for ensembles of the same wind condition. The investigated wind condition were chosen as follows. The 10min-average wind speed is between 7.5m/s and 8.5m/s. The 10min-average wind direction is in the \(15^\circ\) westerly sector between \(262.5^\circ\) and \(277.5^\circ\). The measured 10min-average wind speed and the 10min-based second-order moment of wind speed are obtained from the nacelle anemometry of wind turbines. The wind direction is measured at the meteorological mast south of the wind turbine row on turbine hub height. The measurements are filtered according to the above described sectors of average wind speed and wind direction. The spatial variance of the second-order moment of axial wind speed \(\delta \mu_{2,u,X-D08}\) is defined with reference to wind turbine D08 as

\[
\delta M_{2,u,X-D08} = \sqrt{\langle (\mu_{2,u,X} - \mu_{2,u,D08})^2 \rangle / \langle \mu_{2,u,D08}^2 \rangle}
\]  

(3.11)

where \(\mu_{2,u,D08}\) and \(\mu_{2,u,X}\) are the second order moments of axial wind speed measured at wind turbine D08 and one of the other front-row wind turbines, respectively. Figure 3.3 shows the spatial variance of the second-order moment between the front-row wind turbines E07, F06, G05, H04 and wind turbine D08. The spatial variance is normalized by the ensemble variance of axial wind speed at wind turbine D08. The results are binned with respect to turbulence intensity. The results of each bin are based on at least 33 distinct measurements.

It can be observed that the measured spatial variance of the second-order moment ranges between 25% and 30% between wind turbines E07 and D08. The results are thus comparable to results of the analytic solution and of the simulation, which show a spatial variance of 34% and 35% respectively. The lower spatial variance observed in the field data can be due to differences in the power spectrum of wind speed, which can mainly occur out of two reasons. First, the characteristics of the ABL used in the simulations of this work are likely to be different from the conditions in the measurements. Second, the Mann model used in the simulations and analytic solution of this work provides spectra of undisturbed atmospheric flow. The measurements, however, are made on the nacelle of a wind turbine, where the rotor and nacelle of the wind turbine disturb the flow. The spectrum of wind speed measured at the nacelle of a wind turbine is expected to contain more energy at higher frequencies than the free flow. In [71] this is shown for the near wake, where the energy in the spectrum of wind speed is increased particularly at higher frequencies. Thus, in the nacelle-based measurements an increased share of the power of higher frequency eddies is expected in the second-order moment. The spatial variance of the second-order moment of wind speed, however, is
expected to not originate from turbulent eddies of higher frequencies. This is because the ensemble average of the power of such eddies is considered to be captured well by the 10min measurement duration. Therefore, the variance between measurements of the second-order moment on the nacelle of adjacent wind turbines is expected to be smaller than in the free flow, as observed in the results.

Figure 3-3 further shows the effect of the separation distance and atmospheric stability on the spatial variance of the second-order moment. Atmospheric stability is implicitly characterized by turbulence intensity. Larger turbulence intensity is likely to correspond to more unstable atmospheric conditions. For turbulence intensities ranging between 7% and 8%, a larger distance between the turbulence measurement location does not result in a clear trend in spatial variance of the second-order moment. The measurements are thus comparable to the results based on simulations and the analytic solution, where the spatial variance already reaches the asymptotic value for the spacing between turbines E07 and D08. For a turbulence intensity between 8% to 10% a convergence of the spatial variance to an asymptotic value can be observed. With the separation distance of 1400m between turbines G05 and D08, the spatial variance of the second-order moment reaches the asymptotic value, and stays constant with the larger separation distance of 1850m between turbines H04 and D08. This verifies that the convergence to an asymptotic value observed in the analytic solution and simulations is also observed in the field. However, the asymptote is reached at a seven times larger separation distance and a 90% larger magnitude of the spatial variance of the second-order moment. This is because of mesoscale meteorological effects present in the field that are outside of the scope of the Mann model. The higher turbulence intensity of 8% to 10% indicates a more unstable condition of the ABL. As a result, there is more power in large eddies
of a scale comparable to the separation distance of the wind turbines [68]. As these are mesoscale meteorological effects they are outside of the scope of the Mann model.

To conclude, the field results demonstrate the validity of the analytic solution and simulation results. Further, it can be observed that in more unstable atmospheric conditions the spatial variance of the second-order moment of wind speed can be 48%. Finally, the results show that the use of the average turbulence intensity at upstream turbines as input to a control-oriented flow model would introduce a random error. It can be shown using the SWM wind farm operation model that the thereby resulting error in the prediction of power at a downstream turbine can be in the same order of magnitude as the error in turbulence intensity. More information on the SWM model can be found in [1] or section 5.2.1 of this thesis. To mitigate this random error, a solution can be to use the turbulence measured at each turbine location as input to the flow model, as used in [59][72]. Thereby, the local realizations of turbulent structures can be taken into account.

Verification of Wind Turbine Performance

The turbulence intensity in the flow approaching a wind turbine influences the fatigue loads [61][62] and power output [50][51][63] of the wind turbine. Hence, turbulence intensity measurements are used in the verification of the performance of wind turbines. Turbulence intensity is defined according to the IEC norm [58] as the ratio of the square root of the second-order moment of axial wind speed $u$ to the average of wind speed $u$ calculated for a period of 10min. Uncertainty in the measured second-order moment of wind speed propagates to the measured power output and fatigue loads. A contributor to such uncertainty is the spatial variance of the second-order moment of wind speed.

In the following the spatial variance is quantified for a typical set-up used for the verification of wind turbine performance. The results give insight into the impact of the spatial variance on the uncertainty in power output and fatigue loads.

Figure 3-4 shows a typical, experimental set-up used for the verification of the performance of a wind turbine. A meteorological mast adjacent to the wind turbine is used for the measurement of the flow that approaches the wind turbine. In the present study, the distance between the mast and the wind turbine is set to 200m, which is a magnitude comparable to real set-ups. Two cases on the alignment between the mean wind direction and the mast and the wind turbine are shown in the figure. In the case of alignment, the turbulence structures measured at the mast are experienced by the wind turbine given the assumption of Taylor’s hypothesis of frozen turbulence. As a result, the second-order moment of wind speed measured at the mast is the same as faced by the turbine. Thus, the spatial variance of the second-order moment is zero in this case.

In the case of misalignment, the spatial variance increases with larger misalignment, as shown in Figure 3-5. The figure shows the effect of the misalignment angle on the RMS random error in the measured second-order moment at the mast. The misalignment angle is defined as the angle between the wind direction and the line connecting mast and turbine. The results are obtained from simulations based on the Mann model. The simulation set-up and atmospheric conditions are the same as described in section 3.3.1.
Figure 3-4: Effect of inflow angle on lateral offset of meteorological mast from wind turbine. Lateral offset is distance orthogonal to direction of wind flow. Source: [J2]

Figure 3-5: Effect of misalignment angle on random, RMS error in extrapolation of measured second-order moment of wind speed to wind turbine location. Distance between wind turbine and meteorological mast is 200m, as described in Figure 3-4. Source: [J2]
With misalignment, the flow measured at the mast is offset to the flow, that the wind
turbine faces, in the cross-axial direction. As shown in Figure [3-1] such offset results
in a spatial variance of the second-order moment of wind speed. Thus, the second-
order moment of wind speed measured at the mast is associated with a random error
considering the second-order moment present at the wind turbine for reference.

It can be observed that the random error increases rapidly with increasing misalignment.
The error reaches 90% of the asymptotic value at a misalignment of $22^\circ$, $22^\circ$, and $11^\circ$
for the second-order moment of the wind velocity components $u$, $v$, and $z$, respectively.
The asymptotic value of the error is 36%, 18% and 16% for the second-order moment
of the wind velocity components $u$, $v$ and $z$, respectively.

It is therefore of interest to investigate the impact of such random error on the measured
fatigue loads and power output of the wind turbine. In [61] it is reported that a 70%
increase in turbulence intensity resulted in an approximately tenfold increase in the
fatigue damage fraction of the flapwise blade-root bending moment. In [62] a variance
of turbulence intensity of 22.8% resulted in a variance of the DEL of the yaw moment of
12.7%. It is therefore concluded that uncertainty in the measured turbulence intensity
can have a significant impact on the uncertainty in the measured fatigue loads. The
impact of turbulence intensity on the power curve depends on the operational region
of the wind turbine. In [51] it can be observed that the sensitivity of the power curve
to turbulence intensity is small when the turbine is operating below the rated rotational
speed. In operation at the rated rotational speed, the sensitivity is larger.

In order to quantify the effect of turbulence intensity on turbine performance more ac-
curately, two methods can be applied to mitigate the impact of the spatial variance of
the second-order moment. The measurements can be filtered to only contain data for
small misalignment between wind direction and the line connecting mast and wind tur-
bine. As shown in Figure [3-5] the error increases rapidly with misalignment. Thus, to
limit the error to, for example, below 15%, the misalignment angle could be filtered for
the range of $\pm 5^\circ$. Another approach is to use the ensemble average of turbine perfor-
ance to mitigate the random error. As such, the measurements of turbine performance
are classified according to mean wind speed, mean wind direction, turbulence intensity
and atmospheric stability. The ensemble of turbine performance measurements for a
set of these wind conditions is then averaged. The obtained mean performance of the
wind turbine is less affected by the spatial variance of the second-order moment.

Sensor Verification in Wind Farms

The development of new sensors for application in wind farms can involve testing these
with distant reference measurements. For example, the use of rotor-effective wind speed
to quantify turbulence intensity at a wind turbine was compared to measurements at
adjacent meteorological masts [52]. As shown in the previous section in Figure [3-5]
a small misalignment of the wind direction with the line connecting mast and wind
turbine can result in a large random error in the measured second-order moment. The
same measures as proposed in the prior section can be used to mitigate the impact
of the spatial variance of the second-order moment. These are to filter for direction
misalignment or to average over ensembles of the same atmospheric conditions.

### 3.4 Summary

The first analytical solution for the quantification of the spatial variance of second-order moment of wind speed was developed in this work. The approach is successfully verified using simulation and field data. The impact of the spatial variance of the second-order moment of wind speed is then investigated in three, selected applications of the wind energy sector including mitigation measures. First, the variance of the second-order moment between front-row wind turbines of Lillgrund wind farm is investigated. The variance ranges between 25% and 48% for turbulence intensities ranging from 7% to 10%. Using the average turbulence intensity at front-row turbines as estimate for ambient turbulence intensity would thus result in a random error in flow models. It is thus suggested to use the second-order moment measured at each individual turbine as input to flow models in order to mitigate the random error. This is particularly of importance for dynamic flow models used for wind farm control as these aim to capture the dynamics of flow rather than average properties. Second, the impact of the spatial variance of the measured second-order moment on the verification of wind turbine performance is investigated. Misalignment between the mean wind direction and the line connecting the meteorological mast and wind turbine results in a random error in the observed second-order moment. Such random error brings uncertainty in turbulence intensity-based classification of the fatigue loads and power output of the wind turbine. To mitigate the random error, it is suggested to either filter the measured data for low angles of misalignment or to quantify wind turbine performance using the ensemble average over the same wind conditions. Third, the verification of sensors in wind farms can involve distant reference measurements. In case of a misalignment between the wind direction and the line connecting sensor and reference, a random error will hamper the comparison of second-order moments measured at distant locations. Similar to the verification of turbine performance, filtering the measured data for low angles of misalignment or using the ensemble average, can mitigate the random error.

To conclude, the comparison or combination of measurements of the second-order moment of wind speed from spatially separated locations can result in a random error. Assuming Taylor’s hypothesis of frozen turbulence, the random error is particularly prominent for the separation in the cross-axial and vertical direction of measurement locations. This work shows that knowledge of the drivers of the random error allows for mitigation measures.
Three, innovative developments are presented in this chapter, which offer successful solutions to key challenges of power control of wind farms. First, a control-oriented, dynamic, linear wind farm flow and operation model, is investigated. The developed approach allows to accurately model the future, control-dependent evolution of wind farm flow for its use in power control of wind farms. Furthermore, the employed modelling strategy results in a computationally fast execution. Second, a model-predictive dispatch function for power controllers of wind farms is introduced. The developed approach allows operating the wind farm with respect to multiple objectives, while ensuring that the primary control objective is achieved, that is to follow a reference for the total power of the wind farm. Finally, a model-predictive controller is presented that allows for the reduction of wind turbine fatigue loads.

4.1 Dynamic Flow Predictor

The aerodynamic interaction between wind turbines grouped in wind farms results in wake-induced power loss and fatigue loads of wind turbines. To mitigate these, wind farm control should be able to account for those interactions, typically using model-based approaches. Such model-based control approaches benefit from computationally fast, linear models and therefore, in this work the Dynamic Flow Predictor (DFP) is introduced. It is a fast, control-oriented, dynamic, linear model of wind farm flow and operation that provides predictions of wind speed and turbine power. The model estimates wind turbine aerodynamic interaction using a linearized engineering wake model in combination with a delay process. The DFP is tested on a two-turbine array to illustrate its main characteristics and on a large-scale wind farm, comparable to modern offshore wind farms, to illustrate its scalability and accuracy in a more realistic scale. The simulations are performed in SimWindFarm (SWF) with wind turbines represented using the NREL 5MW model. The results show the suitability, accuracy and computational speed of the modelling approach. In the study on the large-scale wind farm, rotor-effective wind speed is estimated with a NRMSE error ranging between 0.8% and 4.1%. In the same study, the computation time per iteration of the model is on average $2.1 \times 10^{-5}$ s. It is therefore concluded that the presented modelling approach is well suited for the use in wind farm control.
4.1.1 Introduction

The wind energy market has been growing rapidly at a rate of 16% throughout the past decade reaching 539,123MW of global, installed capacity in 2017 [3]. Modern wind turbines are complex machines with sophisticated control systems. Single turbine control systems are well developed and most of the modern machines are, at least to some extent, optimized in the areas of aerodynamics [7], aeroelasticity [8] and control [54]. When grouped in wind farms, the individual optimal operation does not necessarily coincide with the overall optimum, mainly due to the aerodynamic interaction between the wind turbines. Control actions on one wind turbine may impact the performance of another wind turbine in its vicinity, hence considering such interaction effects is beneficial in wind farm control. The operation of the whole wind farm is optimized in wind farm control by using a coordinated control algorithm that specifies the operation point of each turbine. Common objectives of wind farm control are (i) to maximize the total power of the wind farm [46,47] or (ii) to follow a specified reference for the total power of the wind farm that is termed power control [15,16]. The control objectives can be augmented to include multi-objective optimization that simultaneously also aims to reduce the fatigue loads of wind turbines [17,18], [J4]. In approaches of wind farm control with the objective of the maximization of the total power, it is crucial to consider the aerodynamic interaction of wind turbines in the model employed for control [73],[C4].

The turbulent nature of wind farm flow [71] drives the benefit of predicting wind speed dynamics at wind turbines in certain areas of wind farm control. Investigated prediction approaches are individual turbine-based prediction [29,74,75] and wind farm-scale, dynamic flow models [26,76]. The former approaches use measurements at the respective wind turbine or in the turbine’s proximity to predict the evolution of wind speed at that turbine. The prediction is performed using statistical models [29,77] and / or machine learning [78]. An overview of relevant prediction methods can be found in [79]. Such individual turbine-based prediction does, however, not model the aerodynamic interaction of wind turbines.

With regards to power control of wind farms, model-free [15,16] and model-based approaches [17,18], [J4] are investigated in literature. Model-based approaches typically employ dynamic models, since they result in a superior performance as compared to static models [20]. The use of model-based approaches for power control of wind farms can provide several advantages over model-free approaches. First, the use of models of the aerodynamic interaction of wind turbines allows to optimally distribute the extraction of kinetic power from wind flow in space and time in a wind farm. This is beneficial when, for example, the available power of the wind farm is larger than the requested total power. Then, the excess power can be used later when the available power of the wind farm does not suffice. This can be achieved by reducing the power of upstream turbines in order to provide the power to downstream turbines at later time instances. Second, wind farm-scale flow models used in power controllers can provide accurate predictions of wind speed at wind turbines, which can be employed to
estimate a turbine’s available power or fatigue load dynamically. Such estimates can be used to optimally distribute turbine power set-points in a wind farm and to reduce turbine fatigue.

A variety of dynamic, wind farm-scale flow models are investigated in literature. These models are based on either engineering wake models or two-dimensional CFD. The latter models estimate hub height wind farm flow using customized, two-dimensional Navier-Stokes equations. A value proposition of such models is that wind farm flow is not only estimated at turbine locations, but in the entire hub height plane of the wind farm. The use of a CFD model is, however, typically more computationally expensive than the use of engineering models of wind farm flow. Engineering models have been investigated for model predictive control of wind farms, with good results that can perform wind farm-scale optimization in the order of minutes. In the quest of further reducing the duration of the optimization, a natural step is to move towards linear control approaches, such as linear model predictive control. To do so, one will need a linear, dynamic model of the wind farm flow. Few literature is available so far on this subject. A linear wind farm model that includes a dynamic turbine model, that is time-varying axial induction factors and yaw misalignments, and wake characteristics is presented in. Another application of linear model predictive control approach is shown in where the aim is to minimize the wind turbine mechanical loads using a dynamic, linear wind farm flow and operation model. The authors conclude that the benefits of a linearized flow model approach are promising and indicate directions for further research.

The contribution of the present work is the introduction of a novel approach for a dynamic, linear model of wind farm flow and operation, the DFP. The approach allows for both the accurate prediction of turbine power and wind farm flow. The flow model is a linear version of the engineering model-based approaches successfully demonstrated in. The linear nature of the model and the use of an engineering wake model results in low computational cost.

The structure of this section is as follows. Next, the methodology is detailed. Thereafter, the performance of the model is discussed in two case studies. The section concludes with a summary of the key findings.
4.1.2 Methods

The newly developed DFP and the simulation environment used for its testing are described in the following.

**Dynamic Flow Predictor**

The DFP is a dynamic, linear, discrete time wind farm operation model, which consists of a model of wind farm flow and turbine power, with system structure as shown in Figure 4-1. A Kalman filter and a dynamic model update process are used to improve the accuracy of the model.

![Figure 4-1: System structure of DFP showing system update process and Kalman filter time update and data update. Source: [J3]](image)

**Turbine Operation Model**  A static representation of the wind turbine is used and as such it follows turbine power set-points without delay. As shown in Figure 4-1, turbine power $P$ is modelled using a direct feed-through. As such, the modelled turbine power output $P_{out}$ equals the turbine power set-point $P_{set}$ as long as the turbine power set-point is in the range of the turbine’s available power.

$$
P = P_{out} = \begin{cases} 
    P_{set}, & \text{if } 0 \leq P_{set} \leq P_{avail}, \\
    0, & \text{if } 0 > P_{set}, \\
    P_{avail}, & \text{if } P_{avail} < P_{set}. 
\end{cases}
$$

(4.1)
$P_{\text{avail}}$ is the available power of a wind turbine \cite{72}, which is calculated as

$$P_{\text{avail}} = \frac{1}{2} \rho A_{\text{rotor}} u^3 c_{P, \text{max}}$$ \hfill (4.2)

where $\rho$ is the air density, $u$ the rotor-effective wind speed and $c_{P, \text{max}}$ the maximum power coefficient of the turbine achievable at the present wind speed. The assumption of modelling turbine power using a direct feed-through is valid if relevant turbine dynamics are either much faster or much slower than the sampling time. The sampling time recommend for the DFP is thus 30s. The relevant, in this case, fast turbine dynamics are generator power dynamics and blade pitch control dynamics, which are typically in the order of seconds. It is thus assumed that the dynamics of turbine power production can be modelled using algebraic variables.

**Flow Model**  Out of the dynamic phenomena of wind farm flow those potentially relevant for control-oriented modelling are wake propagation, wake meandering and turbine induction. The dynamics of induction of wind turbines settle below time spans of 10s \cite{80}. Given the recommended sampling time of 30s, such dynamics are not considered in the DFP. Wake meandering is modelled in a time-averaged manner by using engineering wake models \cite{25} in the DFP. The dynamics of wake propagation are explicitly modelled in the DFP flow model. The approach of the DFP for the modelling of wake propagation, wake meandering and turbine induction was also employed in \cite{23,25}, and successfully validated in these works using Supervisory Control And Data Acquisition (SCADA) data from wind farms and LES. In the present work, we introduce a linear version of such approach, which is thereby well suited for linear control methods.

The flow model estimates the future wind speed at turbines that do not face upstream wake flow using a persistence-based estimate. The aerodynamic interaction of one or multiple upstream turbines with a downstream turbine is modelled as

$$u_i[n] = u_\infty[n - \Lambda_\infty] - \sum_{l \in \Upsilon_i} \delta u_{i,l}[n - \Lambda_{i,l}]$$ \hfill (4.3)

where $u_i$ is the rotor-effective wind speed of downstream turbine $i$ at discrete time $n$. The rotor-effective wind speed is the wind speed in the mean wind direction averaged over the rotor area of a wind turbine. All wind speeds in section 4.1 on the DFP are rotor-effective wind speeds. $u_\infty$ is the wind speed at the most upstream turbine and $\delta u_{i,l}$ is the wake deficit induced by upstream turbine $l$ to downstream turbine $i$. $\Upsilon_i$ is the set of all turbines upstream of turbine $i$. $\Lambda_\infty$ is the discrete time delay for the wake of the most upstream turbine to propagate to downstream turbine $i$. $\Lambda_{i,l}$ is the discrete time delay for the wake of upstream turbine $l$ to propagate to downstream turbine $i$. The discrete time delay $\Lambda$ is defined as the integer-rounded ratio of the wake propagation delay $\delta t$ and the sampling time $T_s$ as $\Lambda = (\delta t/T_s)_{\text{round}}$.

The duration of wake propagation $\delta t$ can be determined in different ways, while the
overall aim is to choose the model that matches the wind farm in question as close as possible. In this work, we use an engineering model [81]. In the simulation model, SWF, which is used for the testing of the DFP, the wake propagation speed is proportional to freestream flow. Thus, the model for the wake propagation delay \( \delta t \) is chosen for this work to be calculated as \( \delta t = \delta x / u \), where \( u \) is the measured wind speed and \( \delta x \) the distance of the propagated wake.

The wake deficit is modelled based on the Frandsen wake model [82], which estimates the wake deficit \( \delta u_{i,l} \) as

\[
\delta u_{i,l} = \frac{1}{2} c_T(P, u_l) \left( 1 + \frac{\delta x}{4R_l} \right)^{-1} \frac{A_{overlap,l,i}}{A_{rotor,i}} \tag{4.4}
\]

where \( c_T \) is the thrust coefficient, \( P \) is the turbine’s power and \( \delta x \) the distance from turbine \( l \) to turbine \( i \) in the mean wind flow direction. \( R_l \) is the radius of the rotor of the upstream turbine. \( A_{overlap,l,i} \) is the overlap area of the wake from upstream turbine \( l \) with the rotor area of downstream turbine \( i \). \( A_{rotor,i} \) is the rotor area of downstream turbine \( i \).

The Frandsen model is chosen as the same wake deficit model is used in the simulation environment, but other wake models can be used similarly. Given the multitude of wake deficit models available in literature, the aim is generally to choose the model that matches the considered wind farm as close as possible. More details on the sensitivity of the accuracy of the DFP to the chosen wake deficit model are discussed in section 4.1.3. The linearized wake deficit, as used in Eq. 4.3, is modelled using the 1\textsuperscript{st} order Taylor series expansion of the wake deficit model as

\[
\delta \tilde{u}_{i,l} = \delta u_{i,l,0} + \frac{\partial \delta u_{i,l}}{\partial u_l} \bigg|_{x_0} \Delta u_l + \frac{\partial \delta u_{i,l}}{\partial P_l} \bigg|_{x_0} \Delta P_l \tag{4.5}
\]

where \( \Delta u_l \) is the deviation of \( u_l \) from the wind speed linearization point \( u_{l,0} \). \( \Delta P_l \) denotes the deviation of turbine power \( P_l \) from the power linearization point \( P_{l,0} \), and \( x_0 \) is the overall system linearization point. The partial derivatives of the Frandsen wake deficit model with respect to wind speed and turbine power are

\[
\frac{\partial \delta u_{i,l}}{\partial u_l} \bigg|_{x_0} = \frac{1}{2} \left( 1 + \frac{\delta x}{4R_l} \right)^{-1} \frac{A_{overlap,l,i}}{A_{rotor,i}} \left( c_T(P_{l,0}, u_{l,0}) + u_l \frac{\partial c_T}{\partial u_l} \bigg|_{x_0} \right) \tag{4.6}
\]

\[
\frac{\partial \delta u_{i,l}}{\partial P_l} \bigg|_{x_0} = \frac{1}{2} \left( 1 + \frac{\delta x}{4R_l} \right)^{-1} \frac{A_{overlap,l,i}}{A_{rotor,i}} \frac{\partial c_T}{\partial P_l} \bigg|_{x_0} \tag{4.7}
\]

The partial derivatives of the wake deficit model (Eq. 4.6 and Eq. 4.7) are used in the linearized wake deficit model (Eq. 4.5), which is employed in the wake superposition model (Eq. 4.3). After converting the wake superposition model to state space form and
joining all wake interaction processes, the total wind farm flow model can be written as

\[
\begin{bmatrix}
\bar{u}_{\text{del, all}} \\
\bar{u}_0
\end{bmatrix}[n+1] = \begin{bmatrix}
A_{\text{del, all}} + B_{u, all} C_u & B_{u_0, all} \\
0 & I
\end{bmatrix} \begin{bmatrix}
\bar{u}_{\text{del, all}} \\
\bar{u}_0
\end{bmatrix}[n] + \begin{bmatrix}
B_{\Delta P, all}\
0
\end{bmatrix} \Delta \vec{P}[n] \tag{4.8}
\]

\[
\bar{u}[n] = \begin{bmatrix}
C_u \\
C_{u, tot}
\end{bmatrix} \begin{bmatrix}
\bar{u}_{\text{del, all}} \\
\bar{u}_0
\end{bmatrix}[n] \tag{4.9}
\]

\(\bar{u}_{\text{del, all}}\) is the wind speed delay states of all wind turbines, \(\bar{u}_0\) is the wind speed linearization point. Output of the flow model is the current rotor-effective wind speed \(\bar{u}\) at the turbines in the wind farm. \(\Delta \vec{P}\) is the deviation of the turbine power set-points from the power linearization point. Matrix \(A_{\text{del, all}}\) models the process of wake propagation delay of all turbines and matrices \(B_{u, all}\), \(B_{u_0, all}\) and \(B_{\Delta P, all}\) model the effect of wake deficit on wind flow. Matrix \(C_u\) relates the wind speed states \(\bar{u}_{\text{del, all}}\) to the current rotor-effective wind speed \(\bar{u}\) at the turbines in the wind farm.

In the following the total system state space model as presented in Eq. (4.8) and Eq. (4.9) is summarized as

\[
\bar{x}[n+1] = A\bar{x}[n] + B\vec{v}[n] \tag{4.10}
\]

\[
\bar{u}[n] = C_{u, tot}\bar{x}[n] \tag{4.11}
\]

where \(\bar{x}\) is the state vector and \(\vec{v}\) is the control input vector. \(A\) and \(B\) are system process matrices and \(C_{u, tot}\) is the wind speed output matrix.

**Kalman Filter and System Update** The process to update the state space model is structured into three steps: (1) Time update, (2) data update and (3) system matrix update. The first two steps constitute a Kalman filter \([83]\). The Kalman filter is used to improve the prediction accuracy of the DFP by correcting the states of the flow model. A Kalman filter is chosen as it allows correcting the system states using a weighted average of measurements of selected states, with more weight given to measurements with larger certainty.

**Time Update** First, in the time update of the Kalman filter the state estimate from the prior time step \(n - 1\) is used to predict the current system state at time step \(n\) based on the system model of time step \(n - 1\). The time update is calculated as
\[ \vec{x}|_{n-1}[n] = A|_{n-1}\vec{x}|_{n-1}[n-1] + B|_{n-1}\vec{v}[n-1] \tag{4.12} \]

where \( \vec{x}|_{n-1} \) is the state estimate condition to measurements up to time step \( n-1 \). Similarly, \( A|_{n-1} \) and \( B|_{n-1} \) are system matrices at time step \( n-1 \). The variance of the state estimate, \( S \), is updated as

\[ S|_{n-1}[n] = A|_{n-1}S|_{n-1}[n-1]A^T|_{n-1} + R_1|_{n-1} \tag{4.13} \]

where \( R_1 \) is the covariance of the process error. The covariance is estimated using physics-based estimates of the model errors.

**Data Update** Second, in the data update of the Kalman filter the system state is updated with present system measurements, that are related to system states as

\[ \vec{y}_\text{meas}[n] = C|_{\text{meas}}\vec{x}|_{n-1}[n] \tag{4.14} \]

The estimate of the measurements \( \vec{y}_\text{meas} \) are wind speeds related to selected wind speed states of the flow model, such as the current rotor-effective wind speed at wind turbines. Matrix \( C|_{\text{meas}} \) relates the system states to these measurements.

The Kalman gain \( K \) is calculated as

\[ K|_n = S|_{n-1}[n]C^T|_{\text{meas}}|_{n-1}(C|_{\text{meas}}|_{n-1}S|_{n-1}[n]C^T|_{\text{meas}}|_{n-1} + R_2|_{n-1})^{-1} \tag{4.15} \]

where \( R_2 \) is the covariance of the measurement noise. The covariance is estimated using physics-based and empirical estimates of the measurement errors. The cross-correlation between \( R_1 \) and \( R_2 \) is modelled to be zero. More details on the calculation of the covariance of the process error and measurement error can be found in appendix ??

The data update is performed as

\[ \vec{x}|_n[n] = \vec{x}|_{n-1}[n] + K|_n(\vec{y}_\text{meas}[n] - C|_{\text{meas}}\vec{x}|_{n-1}[n]) \tag{4.16} \]

\[ S|_n[n] = S|_{n-1}[n] - S|_{n-1}[n]C^T|_{\text{meas}}|_{n-1} \]
\[ \times (C|_{\text{meas}}|_{n-1}S|_{n-1}[n]C^T|_{\text{meas}}|_{n-1} + R_2|_{n-1})^{-1}C|_{\text{meas}}|_{n-1}S|_{n-1}[n] \tag{4.17} \]

**Matrix Update** Third, system matrices are updated based on the current system operation point. The update approach depends on the deviation of the current system state from the linearization point. If the deviation exceeds the update limit \( \epsilon_{\text{upd}} \), the system
matrices are updated and as a result the new linearization point equals the current system state. If the deviation is within the limits, the system matrices remain unchanged. Consequently, a matrix update is performed if the following condition is satisfied.

\[ \epsilon_{upd} < \frac{|x - x_0|}{x_0} \]  

(4.18)

where \( x \) represents a relevant system condition such as wind conditions and turbine operation point, and \( x_0 \) the linearization point of that condition. \( \epsilon_{upd} \) is the update limit. Detailed analysis of this and guidelines on choosing the appropriate update limit are discussed in section 4.1.3.

**SimWindFarm Simulation Environment**

The DFP is tested in simulations using the dynamic simulation framework SWF [55, 84].

**Modelling Approach**  SWF performs simultaneous, dynamic simulations of the wind turbines in the wind farm, the wind farm control, the aerodynamic interaction of the wind turbines and the actions by the transmission system operator. The NREL 5MW virtual turbine model [56] is used to model wind turbine operation. Key characteristics of the turbine model are shown in Table 4.1. Wind turbine aerodynamics are modelled using the turbine power coefficient and thrust coefficient [84]. Up to 3rd order dynamic models are employed to simulate the drive train, generator and pitch actuator. The aerodynamic model of the wind flow in the wind farm is structured into an ambient field model and a turbine wake model part. The ambient wind field is modelled as the hub height, turbulent wind flow advected with the mean wind speed under the assumption of Taylor’s frozen turbulence. Wake flow modelling includes wake wind speed deficit, wake width expansion, wake meandering and wake merging. Wind turbines are controlled using the DTU Wind Farm Controller [C5], which is linked to the SWF simulation tool and replaces the basic, standard wind farm controller in SWF.

Table 4.1: Key characteristics of NREL 5MW turbine model used in all SWF simulations.

<table>
<thead>
<tr>
<th>Rated power</th>
<th>Cut-in / rated / cut-out wind speed</th>
<th>Rotor diameter</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 MW</td>
<td>3 m/s / 11.4 m/s / 25 m/s</td>
<td>126m</td>
</tr>
</tbody>
</table>

**Validity as Test Environment**  The use of engineering models for the modelling of the dynamics of wind farm flow was successfully validated in [23, 25], as discussed in section 4.1.2 "Flow Model". The validation of the DFP therefore aims to investigate how well the linearized engineering model of the DFP compares to the nonlinear engineering models of the higher fidelity SWF. The flow model in SWF is more complex. It includes the effects of wake meandering, non-linear, multiple wake modelling and
wake merging, which all are not considered in the \textit{DFP}. The main similarity between the \textit{DFP} and \textit{SWF} is the wake deficit model. Section 4.1.3 evaluates the effect of using a different deficit model in the \textit{DFP}. The results show that the modelling approach of the \textit{DFP} is valid with the use of different deficit models. Second, \textit{SWF} models a variety of turbine dynamics with up to 3rd order dynamic equations, whilst no turbine dynamics are modelled in the \textit{DFP}.

\textbf{Simulation Conditions} The \textit{SWF} simulations in section 4.1 are performed in the same wind conditions. The simulated wind conditions have a mean wind speed of 8m/s, a turbulence intensity of 6%. The wind direction is considered aligned with the turbine row, if not indicated differently in the discussion.

\textbf{4.1.3 Results & Discussion} \\

The \textit{DFP} is tested on a two-turbine array to illustrate its main characteristics and a large-scale wind farm to showcase its application in a realistic configuration.

\textbf{Case Study: Two-turbine Array} \\

In the two-turbine case study the effect of Kalman filtering, and wind direction on the performance of the \textit{DFP} are investigated and the computational efficiency of the \textit{DFP} is discussed. A two-turbine wind farm is chosen as it is the simplest set-up possible to analyze these effects and thereby eases the understanding of the work. In the following, first, the simulation set-up is introduced and second, the case study results are presented.

\textbf{Simulation Set-up} The case study is performed in the dynamic simulation tool \textit{SWF}. Employed wind farm layout and wind farm operation mode are discussed in more detail in the following.

\textit{Wind Farm Layout} The layout of the simulated two-turbine array is shown in Figure 4-2. As such, turbine No. 1 is the upstream turbine and turbine No. 2 the downstream turbine. The turbine array is spaced with 4.3 \textit{D}.

![Figure 4-2: Layout of two-turbine array used for test of \textit{DFP}](image)
**Wind Farm Operation**  In all simulations of this section 4.1 the wind farm is operated in the ancillary service "active power constraint mode" [85]. Both case studies use the same normalized total power reference signal of the "active power constraint mode". The total power reference signal is further chosen as such that the resulting individual turbine power references never exceed a turbine’s available power in any of both case studies.

![Graph of total farm power and available power over time](image)

(a) Total power $P_{tot}$ and available power $P_{rat, wf}$ normalized by the rated farm power $P_{rat}$.

![Graph of blade pitch angle](image)

(b) Blade pitch angle dynamics for turbines No. 1 and 2 over time.

**Figure 4-3**: Simulated operation of two turbine array used for comparison with DFP. Shown are (a) total farm power and (b) blade pitch angle. Source: [J3]

Figure 4-3a shows the simulated total farm power output, the total power reference signal and the wind farm available power for the two-turbine case study. The power is normalized with the rated wind farm power. The wind farm is controlled using the closed-loop PI-controller of the DTU Wind Farm Controller with the equal dispatch function [J1] in both case studies. See section 4.2 for more information on controller. It can be observed, that the total farm power follows the total power reference well. The NRMS deviation from the reference is 0.35%. The wind turbines are controlled using a standard wind turbine control approach [54]. The reduction of the turbines’ power below the available power results in the turbines operating at the rated rotor rotational speed, while controlling aerodynamic power using the pitch controller. Figure 4-3b shows the dynamics of the blade pitch angle of the wind turbines. The observed variation of the pitch angle results in a variation of the turbine’s thrust and consequently, also in a variation of the wake deficit generated by that turbine.
**Results** The benefits of the Kalman filter, the computational efficiency of the DFP and the effect of wind direction on the performance of the DFP are discussed in the following.

**Benefits of Kalman filtering** Tests of the DFP show that the use of the Kalman filter can significantly improve the accuracy of wind speed prediction. Figure 4-4 shows a comparison of the wind speed estimate of the DFP with the test environment SWF. The wind speed is compared at the location of the two turbines. Figure 4-4a shows the wind speed at upstream turbine No. 1. It can be observed that the wind speed prediction by the DFP is in good agreement with SWF. The normalized RMS deviation of the wind speed prediction of the DFP is 4.8% both with and without the use of the Kalman filter. It is evident that there is a time lag of one time step in the wind speed estimates of the DFP both with and without the use of the Kalman filter. This is due to the definition of the wind speed state in the DFP. The wind speed state at a time step \( n \) is defined as the mean wind speed over the time interval \([n T_s, (n+1) T_s]\). The wind speed at the upstream turbine at time step \( n \) is calculated using a persistence-based prediction from the wind speed measurements over the time interval \([(n-1)T_s, nT_s]\). As a result, the DFP wind speed estimate at the upstream turbine has a lag of one time step.

![Figure 4-4: Sampled rotor-effective wind speed simulated using SWF and predicted using DFP with and without use of Kalman filter. Shown are wind speeds of (a) turbine No. 1 and (b) turbine No. 2. Source: [J3]](image)

Figure 4-4b shows the wind speed at downstream turbine No. 2. It can be observed that the DFP predictions of wind speed are in good agreement with SWF. The normalized RMS prediction error is 4.4% without the use of the Kalman filter. The use of the Kalman filter reduces the error by 70% to a RMS error of only 1.3%, as shown in Figure 4-5. The error reduction is achieved as the Kalman filter allows to correct both measurable and not measurable states of the DFP model.

**Computational Efficiency** Model-based control benefits from computationally fast models. Since the DFP was developed for use in model-based control, computational effectiveness is a core characteristic. Low computational cost is achieved by the use of the dynamic model update and the low computation time required for an iteration of the state space system of the DFP. The computation time per iteration is discussed in the large-scale wind farm case study in section 4.1.3, since it is a computationally demanding scenario. The benefit of the dynamic model update is discussed on the two-turbine
array in the following, as the simpler set-up eases the understanding. The dynamic model update decides dynamically on executing updates, as described in section 4.1.2. It thereby aims to reduce computational cost by decreasing the frequency of model updates while retaining the accuracy of the model. The approach is to perform a model update only when the deviation of the system operation point from the linearization point exceeds the user-defined update limit $\epsilon_{upd}$. With larger deviations from the linearization point the difference between the linear model and the real system increases. Hence, it is the aim to choose the update limit as such that deviations from the operation point are small and the linear model remains representative of the behaviour of the real system.

Figure 4-5: RMS deviation of rotor-effective wind speed estimation at turbines of two turbine array. RMS deviation is normalized with mean freestream wind speed. Source: [J3]

The impact of the operational conditions on the update frequency and accuracy of the model is discussed in the following. First, a wide range of wind turbine downregulation is investigated in a simulation study. The study also covers the effect of turbulent wind
speed. Thereafter, the impact of other variations of wind conditions are discussed. The study is conducted in two scenarios of wind farm operation and thereby covers a wide range of downregulation. In both scenarios the two-turbine array is operated in the "active power constraint mode" [85], that is total power of 1.8 MW in scenario 1 and 0.9 MW in scenario 2, as shown in Figure 4-6a. Albeit the total power of the wind farm and the turbine power is constant in the simulation, the turbulent wind speed results in a variation of the turbines’ power coefficient, as depicted in Figure 4-6b. The wind field and the wind farm layout are the same as for the other investigations of the two-turbine case study.

Figure 4-7 shows the effect of the update limit on model update frequency and model accuracy for both operation scenarios. The accuracy is defined as the RMS error of rotor-effective wind speed at downstream turbine No. 2. The error in estimating the wind speed at the upstream turbine is not part of this analysis, since it is not affected by the matrix update. The update frequency is defined as the average ratio of matrix updates $n_{upd}$ to model iterations $n_{iter}$. The study is performed without the use of the Kalman filter, so the estimation accuracy is only dependent on the linearization approach. It can be observed that in scenario 1 the model accuracy is insensitive to the update frequency. In scenario 2, the model accuracy is constant up to an update limit of 0.3. Increasing the update limit from 0.3 to 0.5 results in an increase of model error from 4.5% to 4.9%. Hence, the choice of an update limit of 0.25 for the other investigations of this work, as described in section 4.1.2, appears to be sufficient to retain accuracy. The results also show that the update frequency can be reduced by 100% in scenario 1 and by 97% in scenario 2 without compromising model accuracy.

![Graph showing impact of matrix update limit on downstream turbine wind speed prediction accuracy and matrix update frequency.](source)

Figure 4-7: Impact of matrix update limit on downstream turbine wind speed prediction accuracy (right) and matrix update frequency (left). Source: [J3]

Generally, the extent up to which the update limit can be increased without compromising accuracy depends on the operating conditions, that is the operation point and the dynamic behaviour of the system around it. The dominant dynamics in the present study are variations of wind speed and turbine operation point, illustrated by the power coefficient, as shown in Figure 4-6b. In scenario 1 the power coefficient of the upstream turbine is 0.26 on average and varies with a standard deviation of 18%. In scenario 2
the power coefficient of the upstream turbine is 0.13 on average and varies with a standard deviation of 18%. The power coefficients covered in both scenarios range from 0.07 up to 0.45. As the maximum power coefficient is 0.48, a wide range of turbine downregulation levels is covered by the two scenarios.

The results show that for the dynamic conditions of the present study only few model updates are required to retain model accuracy. It is of interest to understand how other variations of operational conditions relevant for power control of wind farms impact the update frequency. Such variations are changes of turbulence intensity and of the 10min-average wind speed and wind direction, that could be shifts in the order of 1%, 1m/s and 5deg, respectively. Since these changes typically occur at time scales in the order of several minutes, their impact on the update frequency will not be significant. The changes of ABL conditions typically occur at even larger time-scales and are therefore also not having a significant impact on the update frequency.

Effect of wind direction

The impact of the full range of wind directions and wake situations on the accuracy of the DFP is investigated in the following. Figure 4-8 shows the effect of the alignment of the two-turbine array with the mean wind direction on the accuracy of the DFP. In the study the Kalman filter of the DFP is active. In Figure 4-8.a it can be observed that the accuracy at both turbines varies with wind direction. The variation at the upstream turbine is because the wind fields differ between the simulations of different wind directions. Each wind field is based on a distinct turbulence seed and as a result the turbulence intensity varies between the wind fields. It can be shown that this difference in turbulence intensity results in the observed variation of the error of the persistence-based prediction at the upstream turbine.

![Figure 4-8: Effect of alignment of turbine array with wind direction on accuracy of estimation of rotor-effective wind speed. Shown are (a) accuracy for each turbine and (b) ratio of RMS wind speed estimation error at downstream turbine to RMS wind speed estimation error at upstream turbine. Source: [J3]](image)

The turbulence intensity-driven variation of the error in the prediction of wind speed at the upstream turbine propagates to the error in the prediction of wind speed at the downstream turbine. To remove this effect and allow to focus on the impact of wind direction, Figure 4-8.b shows the ratio of these errors. As such, the RMS error for the downstream turbine is normalized by the RMS error for the upstream turbine. It can be observed
that the accuracy of wind speed prediction for the downstream turbine decreases with an increase in wind direction misalignment. With larger misalignment, the correlation of the wind speed of the two turbines decreases and thus results in an increasing error of the model. Nonetheless, the error at the downstream turbine is smaller than the persistence-based prediction error at the upstream turbine. At $20^\circ$ misalignment the wake from the upstream turbine is not affecting the downstream turbine. Hence, the wind speed estimate at turbine No. 2 is also a persistence-based wind speed estimate. Since both turbines use persistence-based estimates, the ensemble average of the wind speed estimation error is expected to be the same at both turbines. The observed higher prediction accuracy at the downstream turbine is likely to be due to the seed of the turbulent wind field in SWF.

To conclude the two-turbine case study, the above investigations show the benefit of the Kalman filter and the dynamic model update, and the suitability of the DFP for different wake situations.

Case Study: Large-scale Wind Farm

In the large-scale wind farm case study, the performance of the DFP is demonstrated in key areas relevant to the model’s application to large wind farms. The model’s performance is analyzed with respect to its accuracy in the prediction of wind speed and available turbine power. Additionally, the sensitivity of the accuracy of the DFP with respect to the employed wake deficit model is discussed. The layout of the wind farm is depicted in Figure 4-9. The spacing of the wind turbines is five rotor diameters between both rows and columns of the square-grid wind farm layout. The wind farm comprises 80 NREL 5MW wind turbines [56].

Benefit of Kalman filter Figure 4-10 shows the accuracy of the DFP in estimating the wind speed at the turbines of the large-scale wind farm. The accuracy is quantified as the normalized RMS difference between the wind speed estimated by the DFP and SWF. Figure 4-10a provides an overview of the variation of the accuracy across the wind turbines of the wind farm. The results are obtained with the use of the Kalman filter. It can be observed that the accuracy varies between an error of 0.8% and 4.1% at downstream turbines. Along turbine rows the accuracy is similar. This is because the only difference between turbine columns are stochastic differences in the wind field. As a result, the standard deviation of the error within a row is less than 0.5%. The variation of accuracy along turbine columns is larger than along turbine rows. Along columns the accuracy varies due to the difference in the wake deficit summation approach that is employed in the DFP and SWF.
Figure 4-9: Layout of large-scale wind farm used for test of DFP. Source: [J3]

Figure 4-10: Accuracy of DFP in estimation of current rotor-effective wind speed at turbines of large-scale wind farm. Accuracy is quantified as normalized RMS error of wind speed estimated using DFP given SWF as reference. Shown are (a) distribution of accuracy across turbines in wind farm with DFP using Kalman filter, and (b) effect of Kalman filter on row-wise accuracy statistics, that is mean error (bars) and standard deviation of error (errorbars). Source: [J3]
Figure 4-10 shows the effect of the Kalman filter on the row-wise error statistics. The accuracy is quantified as the normalized \textit{RMS} difference between the wind speed estimated by the DFP and SWF. It is observed that the use of the Kalman filter improves the accuracy on average by 57%. The improvement in accuracy varies across turbines. A variation of the improvement in accuracy obtained by the use of the Kalman filter is also reported in [23]. Like in the present study, the work uses the Kalman filter to correct an engineering model-based, dynamic model of wind farm flow.

\textbf{Sensitivity of Wake Model} An important aspect of the DFP is the wake deficit model. Thus, it is of interest to investigate the sensitivity of the accuracy of the DFP to the employed wake deficit model. A comparison is conducted between the use of the Frandsen model, that is the model used for all other studies in this work, and the use of the Jensen model [86]. The wake deficit model employed in SWF remains unchanged, the Frandsen model. Figure 4-11 shows the row-wise statistics of the error in wind speed prediction of the DFP for these two cases.

![Figure 4-11: Effect of wake deficit model on error of DFP in estimation of current rotor-effective wind speed at turbines of large-scale wind farm. Shown are the row-wise statistics, that is mean (bars) and standard deviation (errorbars), of the normalized RMS difference of wind speed between the DFP and SWF. Source: [J3]](image)

It can be observed that the use of the Jensen model increases the error at further downstream turbines. Yet, albeit the larger uncertainty in the wake deficit model, the error of the DFP remains in the same range as with the Frandsen model, that is below 4.5%. The results thus show that the DFP can provide accurate wind speed estimates even with larger uncertainty in the wake deficit model.

\textbf{Wind Speed Prediction} The prediction of wind speed at wind turbines over time horizons in the order of minutes is useful for wind farm control. The analysis of the model’s capability for future wind speed prediction shows that the DFP can provide wind speed predictions with an error of less than 4% over a time horizon of up to 5min.
Reference to the DFP predictions is SWF. Figure 4-12 shows the row-averaged accuracy of the ten-step-ahead prediction of wind speed at the turbines of the large-scale wind farm. Wind speed predictions are calculated using the state space-driven prediction approach employed in model predictive control. The accuracy is quantified using the RMS difference between the DFP predictions and SWF. The results are obtained with the use of the Kalman filter.

Figure 4-12: Accuracy of 10-step ahead prediction of rotor-effective wind speed at rows of large-scale wind farm. Accuracy is normalized RMS difference between DFP prediction and SWF flow model averaged over turbine rows. Kalman filter in DFP is active. Source: [J3]

It can be observed that the low error obtained for prediction step 0 can be sustained over several steps into the future, with more steps at further downstream turbines. After several prediction steps the error raises to a higher level. This can be seen, for example, in Figure 4-12 at turbine No. 4 from prediction step 7 to prediction step 8. The number of steps with low error equals to the number of the model’s internal delay states. Further downstream turbines have a longer accurate prediction horizon due to the larger number of internal delay states. Predictions beyond the model’s internal delay states are based on persistence and thus less accurate. Future work will focus on extending the length of the accurate prediction horizon by exchanging the persistence-based wind speed estimate at the upstream turbine with an individual turbine-focused prediction method such as a statistical model as used in [29].

Available power prediction: The prediction of the turbines’ available power is needed for wind farm control. Figure 4-13 shows the row-averaged RMS error in the prediction of the available power of the turbines of the large-scale wind farm. The available power is calculated using Eq. 4.2 and the wind speed predictions of the DFP as described in section 4.1.3 above. As expected, it can be observed that the pattern in the error of available power prediction is the same as for the analysis of wind speed prediction discussed with Figure 4-12. The error in the prediction of turbine available power ranges between 1.5% to 14%, considering predictions based on the model’s internal delay states only.
Figure 4-13: Accuracy of 10-step ahead prediction of turbine available power for each row of large-scale wind farm. Accuracy is normalized RMS difference between DFP prediction and SWF averaged over turbine rows. Kalman filter in DFP is active. Source: [J3]

**Computation Time**  As described in section 4.1.3, model-based control benefits from the low computation time required per iteration of the state space system of the DFP. To provide a ‘worst-case’ estimate, the computation time is quantified for the computationally-challenging, realistic-scale 80-turbine wind farm. The calculations are performed on a standard personal computer in MATLAB. The available hardware of the computer are one core of a 2.6GHz processor and 8GB installed memory. On average, the computation time per iteration of the state space system is $2.1 \times 10^{-5} \text{s}$.

**4.1.4 Summary**

This section introduces the DFP, a control-oriented, linear dynamic wind farm flow and operation model suited for model predictive control of wind farms. The results of this work show the suitability, accuracy and computational speed of the modelling approach of the DFP. Suitability is given since the DFP can accurately capture the dynamics of wind farm flow in SWF even for complex wind farm configurations. Furthermore, it is demonstrated in literature that engineering models, as used in the DFP, are suited for the prediction of the dynamics of wind farm flow. Accuracy is demonstrated in the control-relevant prediction of wind speed and turbine available power. In the large-scale wind farm case study, the Kalman filter of the DFP reduces the error in wind speed prediction on average by 57%. As a result, current wind speed is estimated with a RMS error ranging between 0.8% and 4.1%. The error of wind speed predictions is less than 4% for a time horizon of 5 min. For the same horizon, turbine available power is predicted with an error ranging between 1.5% and 14%. Beneficial for the computational speed of the DFP is the use of a dynamic model update and the low computation time per state space system iteration. For the investigated, realistic-scale, 80 turbine wind farm, the computation time per iteration is on average $2.1 \times 10^{-5} \text{s}$. Based on the results
presented, we think that the DFP model represents a viable solution for moving wind farm control philosophy towards linear control approaches.
4.2 Model-optimized Dispatch for Power Control

At present, wind farms control their power production by using a closed-loop feedback control approach, which distributes the total power to the wind turbines. However, the total power is distributed according to the turbines’ available power, only. The use of model-predictive control allows to consider multiple objectives, nonetheless, since it is open-loop, it can result in a poor tracking of the total power reference. This work is the first to combine the standard, closed-loop feedback controller with model-predictive optimization in order to yield the benefits of both approaches. As such, we developed an optimization-based dispatch function employed in a closed-loop feedback controller. The dispatch function uses model-predictive, multi-objective optimization to determine the distribution of the total power to the wind turbines. The model employed in the developed dispatch function is the DFP, which uses a Kalman filter-driven feedback to correct the wind farm flow model dynamically. The developed, optimization-based dispatch function is compared to dispatch functions commonly employed in present wind farms in a secondary regulation scenario in dynamic simulation. The comparison is carried out on an eighty-turbine, large-scale wind farm. The newly developed, optimization-based dispatch function yields a reduction of the mean error and the NRMS error by 43% and 36% with respect to the best-performing, commonly-used dispatch function. Furthermore, for the large-scale wind farm, the duration of the model-predictive optimization is only 0.21s, that is two orders of magnitude faster than comparable approaches in literature.

Section 4.2 is based on publications [J1, C2, C3].

4.2.1 Introduction

The wind energy market has been growing rapidly at a rate of 16% throughout the past decade reaching 539,123MW of global, installed capacity in 2017 [3]. The increasing share of renewable power generation sources in the electricity market is replacing conventional generation sources. This change is putting pressure on the power system, as conventional generators are used for providing grid balancing services, historically. However, wind power plants could substitute existing conventional generation sources in providing such grid services [14].

To provide grid balancing services and as such to follow a reference for the total power of the wind farm, power controllers of wind farms typically use closed-loop feedback control. The reference tracking performance of the feedback controller depends on its ability to handle the variable, available power of wind turbines. For example, when a turbine is requested to produce more than its available power, a steady state error results between the power requested from the turbine and its power output. This steady state error at turbine level can translate into a steady state error of the total power of the wind farm from its reference. The power requested from a wind turbine is typically set by the dispatch function of the power controller of the wind farm. The simplest dispatch function is to distribute the total power to the wind turbines using a static distribution. Due to the variability of the available power of wind turbines this approach can result in a poor tracking of the total power reference. In [16] gain scheduling is proposed to mitigate the effect. Another approach is to distribute the total power to the wind turbines proportionally to the turbines’ available power [15]. However, this approach
only considers the availability of aerodynamic power at wind turbines for distributing the total, requested power to the wind turbines.

An alternative control approach investigated in literature is model-predictive control [J4],[17],[20]. The approach has three major advantages. First, it allows to optimize operation according to multiple objectives. As a result, the approach enables to not only follow a reference for the total power of the wind farm, but also to consider other objectives such as to reduce fatigue loads of wind turbines, and to lower the variability of turbine power. Second, model-based control can result in more informed control decisions, and hence potentially in an improved performance. For example, a model can provide the controller with information on the effect of a control action, that is a change in power set-point, on the future evolution of wind speed in the wind farm or on the fatigue loads of wind turbines. Typically employed models are dynamic models of wind farm operation [J3],[20],[21] and models of turbine mechanical loads [J4],[17]. Third, model-predictive control allows to decide on the present control action considering the potential, future trajectories of operation. In [20] it is shown that accounting for the future dynamics of wind farm flow improves the control performance. Despite of these three advantages, there is two impediments to the industrial use of model-predictive control of wind farms. First, since model-predictive control is open-loop, the accuracy of tracking a demanding total power reference is expected to be poor due to the aerodynamic interaction of wind turbines through wakes [22]. Second, most of currently employed dynamic models of wind farm flow are computationally too slow for the use in model-predictive control of large-scale wind farms. Amongst these, engineering models result in the fastest computational speed and a duration of the model-predictive optimization in the order of minutes [20],[23]. Although remarkably fast, such duration still results in a considerable delay in introducing the optimized control actions to the wind turbines.

To address these challenges, the present work introduces a model-predictive, closed-loop feedback controller including a computationally fast model. The controller is a synthesis of the investigated approaches for power control in literature, that is model-predictive control and closed-loop feedback control. The outer control loop is the closed-loop feedback controller that is commonly employed in present wind farms as introduced above. It ensures the accurate tracking of the reference for the total power of the wind farm, allowing it to operate in a mode that ensures available active power reserve to be used in ancillary services. In order to provide the advantages of model-predictive control described above, model-predictive optimization is used in the dispatch function of the closed-loop feedback controller. To reduce the computation time of the model-predictive optimization, a linear model is used, the DFP.

The structure of the section is as follows. Next, the methodology is detailed. Thereafter, the performance of the optimization-based dispatch function is investigated in two case studies. The section concludes with a summary of the key findings.
4.2.2 Methods

First, the closed-loop feedback controller is introduced, second, the static and proportional dispatch functions are discussed, and finally, the model-predictive optimization-based dispatch function is presented.

Closed-loop Feedback Controller

Figure 4-14 shows the system structure of the closed-loop, feedback wind farm controller. The wind farm controller consists of a PI-controller and a dispatch function, which is used to distribute the total power demanded by the PI-controller to the wind turbines.

**PI-controller** The aim of the PI-controller is to track the total power reference signal. The transfer function $C(s)$ of the PI-controller is defined as

$$C(s) = k_p \left(1 + \frac{1}{sT_i}\right)$$  \hspace{1cm} (4.19)

where $k_p$ is the proportional gain and $T_i$ is the time constant of the integrator. An Anti-Windup-Reset set-up is used to limit the integrator with the upper limit set to the wind farm available power.

**Total Power Dispatch** Output of the PI-controller is the demanded total wind farm power, which is distributed to the wind turbines in the wind farm using the dispatch
function. The approach used in the dispatch function for the distribution of the demanded total power $P_{tot, dem}$ depends on the objectives of the wind farm operator. Generally, the demanded total power is distributed to the wind turbines as

$$P_{set,j} = f_j P_{tot, dem}$$  \hspace{1cm} (4.20)

where $f_j$ is the fraction of the total demanded wind farm power dispatched to turbine $j$ and $P_j$ is the power set-point of turbine $j$. $f_j$ is subject to

$$1 = \sum_{j=1}^{J} f_j$$  \hspace{1cm} (4.21)

where $J$ is the number of wind turbines in the wind farm. Three different dispatch functions are considered in the present work, the newly developed model-predictive optimization-based dispatch, and for reference the static dispatch and the proportional dispatch. More details on these are discussed in detail later in this section.

**Controller Tuning**  The tuning of the feedback controller is conducted in three steps, system identification, system analysis an system control.

The transfer function from the power set-points of the turbines to the total power output of the wind farm can be described as

$$P_{tot}(s) = \sum_{j=1}^{J} G_j(s) P_{set,j}(s)$$  \hspace{1cm} (4.22)

where $P_{set,j}(s)$ and $P_{tot}(s)$ are the Laplace-transformed signals of turbine power set-point and of total power output of the wind farm, respectively. $G_j(s)$ is the transfer function, which models the dynamics between turbine power set-point and turbine power output, that is the turbine operation. The transfer function $G(s)$ was identified from the frequency response of the simulated wind turbine to be well represented as a second order system

$$G(s) = \frac{k_G \omega_0^2}{s^2 + 2 \delta \omega_0 s + \omega_0^2}$$  \hspace{1cm} (4.23)

where $\omega_0$ is the bandwidth of the closed-loop turbine control system, $\delta$ the damping factor and $k_G$ the steady state gain of the system. For the conditions used in the case study of this work, see Section 4.2.4, $\omega_0$ and $\delta$ are identified to be 18.3 rad/s and 1.05, respectively. When the turbine power set-point is less or equals to the turbine’s available power, the steady state gain $k_G$ is 1. However, a power set-point larger than the available power of a turbine results in a steady state gain below 1. As shown in [16], the result is
a reduced speed of the closed-loop wind farm system and potentially a steady state error from the total power reference. Therefore, an objective of the dispatch function can be to ensure that the turbine power set-points are not higher than the turbines’ available power. When the power set-points of all turbines are less or equal to the available power of these turbines, \( G_j(s) \) can be assumed to be the same for all turbines. Further, using (4.20), (4.22) can be written as

\[
P_{\text{tot}}(s) = G(s)P_{\text{tot, dem}}(s) \sum_{j=1}^{J} f_j
\]  

(4.24)

Using (4.21) and (4.24), the system controlled by the PI controller is thus modelled as

\[
P_{\text{tot}}(s) = G(s)P_{\text{tot, dem}}(s)
\]  

(4.25)

The PI controller is therefore designed for the system transfer function \( G(s) \). The system \( G(s) \) has two poles with real part smaller than zero and is thus asymptotically stable, as expected. In the present simulation framework, the wind farm controller obtains measurements from the wind turbines at a frequency of 1Hz. Due to the slow sampling frequency, a discrete time controller synthesis is required.

The system \( G(s) \) and the PI controller \( C(s) \) are thus converted to discrete time. \( G(s) \) is converted using a zero-order hold and \( C(s) \) is converted using the Tustin method. The resulting controller transfer function \( C(z) \) is

\[
C(z) = k_p \left( 1 + \frac{T_s}{2T_i} z + 1 \right)
\]  

(4.26)

where \( T_s \) is the sampling time. The poles and zeros of the closed loop system are tuned with the time-domain objective to achieve a fast rise time and no overshoot. The Nyquist plot, depicted in Figure 4-15 shows that the open-loop transfer function \( L(z) = G(z)C(z) \) does not enclose the critical point -1. Since the poles of the open-loop transfer function are located at \( \pi(L(z)) = \{1; 1.8e - 6; 8.4e - 12\} \), the closed-loop system is stable according to the Nyquist criterion. Furthermore, the large minimum distance of 0.7 from the critical point -1 shows the robustness of the closed-loop system.

**Static and Proportional Dispatch**

There are two commonly discussed dispatch approaches in literature for the distribution of the demanded total power. One approach, that is the static dispatch, distributes the demanded total power to the turbines according to a constant distribution that is chosen by the wind farm operator. The second, more advanced dispatch approach is the
proportional dispatch introduced by Hansen et al. in [15]. The proportional dispatch distributes the total demanded power to the turbines using a dynamic distribution function that is based on the available aerodynamic power at wind turbines. The approach thereby aims at ensuring that the power requested from a turbine is less or equal to that turbine’s available power. To distribute the total power proportionally to the turbines’ available power, the value of \( f_j \) is defined as

\[
f_j = \frac{P_{\text{avail},j}}{P_{\text{avail},\text{tot}}}
\]  

where \( P_{\text{avail},j} \) is the available power of turbine \( j \) and \( P_{\text{avail},\text{tot}} \) is the sum available power of all wind turbines in the wind farm.

**Model-predictive Optimized Dispatch**

The advantages of using a dispatch function based on MPO are, as described in the introduction, predictive control and the use of multiple objectives and models of operation. The present work aims to introduce the MPO-based dispatch and therefore the objective function focuses on the most important objective, that is reference tracking used for wind farm ancillary services. The mitigation of wind turbine fatigue loads using a model-predictive controller is presented in the next section 4.3 and in [J4].

**Objective Function** The optimization-based dispatch presented in this work uses MPO to determine the distribution of the total demanded power. The objectives of the MPO cost function \( J \) are to (i) follow the total power reference and (ii) to penalize the variation of the turbine power. The cost function is thus defined as
\[
\mathcal{J}(v) = \sum_{k=0}^{N} \left\{ (P_{\text{tot}}[n + k] - P_{\text{ref}}[n + k])^2 \right. \\
+ \left. \sum_{j=1}^{J} \rho_{\text{rate}}(P_j[n + k] - P_j[n - 1 + k])^2 \right\}
\]  
(4.28)

where \(P_{\text{tot}}[n]\) is the sum power output of all turbines in the wind farm at time step \(n\) and \(P_{\text{ref}}[n]\) the total power reference. \(\rho_{\text{rate}}\) is the weighting factor for the rate of turbine power change, which was tuned by simulation prior to the case study. \(P_j[n]\) is the power output of turbine \(j\) at time step \(n\). The decision variable \(v\) is the power set-points of all turbines over the control horizon \(N\). Generally in this work, the underline denotes that the quantity or matrix spans over the entire prediction horizon.

**Constraints** The turbine power set-points \(v\) are constrained by the availability of aerodynamic power at the wind turbines. Such constraint is of importance, since requesting more power than available from a turbine can result in a steady state error from the reference for the total power of the wind farm. The turbines’ available power is estimated using a newly developed, dynamic, linear model. The model predicts the turbine available power based on wind farm aerodynamics and turbine power set-points. The aerodynamic interaction of wind turbines in the wind farm is modelled using the DFP [J3], as introduced in section 4.1. The future aerodynamic power \(P_{\text{avail}}\) of all wind turbines is calculated as

\[
P_{\text{avail}}(v) = P_{\text{avail},0} + \mathbf{B}_{dP}(u(v) - u_0)
\]  
(4.29)

The matrix \(\mathbf{B}_{dP}\) is a diagonal matrix defined as

\[
\mathbf{B}_{dP} = \text{diag}(\mathbf{B}_{dP}[n], \mathbf{B}_{dP}[n + 1], \ldots, \mathbf{B}_{dP}[n + N])
\]  
(4.30)

\(\mathbf{B}_{dP}\) is a diagonal matrix defined as

\[
\mathbf{B}_{dP} = \text{diag}(\frac{\partial P_1}{\partial u_1}|_{x_0}, \frac{\partial P_2}{\partial u_2}|_{x_0}, \ldots, \frac{\partial P_J}{\partial u_J}|_{x_0})
\]  
(4.31)

where \(\frac{\partial P}{\partial u}|_{x_0}\) is the derivative of turbine power \(P\) to wind speed \(u\) at the operation point of that time step. The derivative of wind turbine power to wind speed is calculated using the turbine’s power curve. The operation point of a wind turbine is estimated using the DFP for each prediction step.

\(P_{\text{avail},0}\) is the baseline, available power of the wind turbines over the prediction horizon. It is calculated assuming that the turbines continue operating at the same, current
power set-points, that is $u_0$. $P_{\text{avail},0}$ is calculated as

$$P_{\text{avail},0} = \frac{1}{2} \rho A c_P \max u_0(v_0)^2$$  \hspace{1cm} (4.32)

where $\rho$ is the air density, $A$ the rotor area and $c_P, \max$ the maximum power coefficient of a turbine. The wind speed predictions $u_0$ are obtained using the DFP as

$$u_0(v_0) = C_u x_0(v_0)$$
$$C_u(A \vec{x} + B v_0)$$

where matrix $C_u$ is used to obtain the wind speed estimate at wind turbines from the state vector $x$ of the DFP state space system. The matrices $A$ and $B$ are defined based on the principles of model predictive control as

$$A = \begin{bmatrix} I \\ A \\ A^2 \\ \vdots \\ A^N \end{bmatrix}$$

$$B = \begin{bmatrix} 0 & 0 & \ldots & 0 \\ B & 0 & \ldots & 0 \\ AB & B & \ldots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ A^{N-1}B & A^{N-2}B & \ldots & 0 \end{bmatrix}$$  \hspace{1cm} (4.35, 4.36)

Finally, using the above derivations, the dynamic, linear available power constraint (4.29) is reformulated to a system of linear constraints that is used for the quadratic programming problem of the MPO (4.28).

### 4.2.3 Case Study: Power Variability & Fatigue Loads

In this case study the performance of the MPO-based dispatch and the proportional dispatch are compared for the operation of the wind farm in the absolute power constraint mode [87]. The comparison provides insights on the impact of the dispatch functions on fatigue loads of wind turbines and power variability. The results of the study also provide indications for the setting of the sampling frequency of the dispatch function. The
static dispatch function is not included in the analysis, because it largely underperforms in delta control operation, as is shown in the subsequent case study.

Simulation Set-up

The case study is conducted on an eight-turbine array, as shown in Figure 4-16. The eight-turbine array can be seen as a column of a large-scale wind farm. Hence, results observed on the eight-turbine array are expected to be similar to those obtained for a large-scale wind farm. The spacing of the turbine array is \( 5D \). The same spacing is used in the subsequent case study.

![Wind turbine array layout](image)

Figure 4-16: Layout of eight-turbine array used to test impact of sampling frequency. Source: [C2]

The operation of the turbine array is dynamically simulated using [SWF] [55]. More information on the simulation model can be found in section 4.1.2 on the DFP. The simulation conditions are a mean wind speed of 8m/s and a turbulence intensity of 8%. The wind farm is operated in the absolute power constraint mode. Consequently, the reference for the total power of the wind farm is constant. This mode is used when grid and / or market constraints, or market bids require to limit the total power output of the wind farm.

In this case study, the frequency of executing the dispatch function in the power controller is set to 0.5Hz to ensure the accurate tracking of the reference. Generally, higher sampling frequencies of the dispatch function result in a more frequent and thus more accurate prediction of the available power of a wind turbine. The higher accuracy in the available power can result in a more accurate tracking of the reference for the total power of the wind farm. To the author’s knowledge - this is the reason for choosing a high sampling frequency of the dispatch function in present wind farms. The chosen sampling frequency of 0.5Hz is at the upper limit at which the system remains stable. At higher sampling frequencies it was observed that the system can become unstable, due to the interaction between the rotor-effective wind speed method and the distribution of power set-points according to the available power of wind turbines, which is estimated from the rotor-effective wind speed.

Results & Discussion

Figure 4-17 compares the tracking of the reference for the total power of the wind farm between the [MPO] dispatch and the proportional dispatch. The figure further shows the available power of the wind farm in relation to the reference signal. It can be observed
that the excess available power above the reference varies between 0 MW and 5MW. As a result, the challenge in distributing the demanded reference total power to the wind turbines differs throughout the simulation. For example, in times with less excess available power it is more challenging to distribute the reference total power to the wind turbines without demanding more power from a wind turbine than available. Despite of the at times low excess available power, the results show that the MPO dispatch and the proportional dispatch allow to follow the reference accurately. Figure 4-17a shows the performance of the MPO-based dispatch. It can be observed that the reference is followed with seemingly no error when the difference between the available power of the wind farm and the reference is large. At times, that the available power becomes more scarce, the variability of the total power output increases. This is because it is more challenging to distribute the reference total power to the wind turbines. Figure 4-17b shows the performance of the proportional dispatch. It can be observed that the reference is followed accurately with some variability in the total power output. The variance of the power output is similar throughout the simulation and does not depend on the excess available power as for the MPO-based dispatch. More details are discussed in the investigation of the turbine power output in the following.

Figure 4-17: Effect of dispatch function on following of reference for total power of wind farm. The compared dispatch functions are (a) MPO-based dispatch and (b) proportional dispatch. Source: [C3]

Figure 4-18 shows the effect of the dispatch function on the power output of wind turbines. Figure 4-18a shows the turbine power output in operation with the MPO dispatch. It can be observed that the power output is constant at times with sufficient excess available power. Thus, there is no need to change the distribution of power set-points. During periods when the excess available power is low at some wind turbines, the set-points of wind turbines are distributed dynamically. Hence, the MPO dispatch adjusts the power output of wind turbines only when necessary. In Figure 4-18b the power output of wind turbines in operation with the proportional dispatch is shown. It can be seen that the power output of wind turbines varies throughout the entire simulation period. The variations are proportional to the available power of wind turbines. This aims to reduce the probability that the power requested from a wind turbine exceeds its available power. Thereby, the turbine power however also varies at times when there is no need for it, due to sufficient excess available power at wind turbines. The frequent
change of the distribution of power set-points by the proportional dispatch is the driver for the variations of the total power output. With every change in the distribution, the controller of each turbine adjust the power output of the turbine. The resulting overshoot in the power output of the individual turbines adds up and creates the variations in the total power output.

Figure 4-18: Effect of dispatch function on power output of wind turbines of eight-turbine array. The compared dispatch functions are (a) MPO-based dispatch and (b) proportional dispatch. Source: [C3]

Figure 4-19: Impact of dispatch function on (a) fatigue loads of wind turbines and (b) STD of power output of wind turbines. Source: [C3]

The observed difference in the distribution of turbine power set-points by the dispatch functions impacts the variability of turbine power and fatigue loads of wind turbines, as shown in Figure 4-19. In Figure 4-19b the standard deviation of turbine power output is shown. It can be observed that the standard deviation is lower in operation with the MPO dispatch at all wind turbines, on average by 53%. This shows that the MPO-based dispatch can be used to reduce the variability of turbine power in the absolute power constraint mode. Figure 4-19a shows the DEL of the fore-aft tower bending moment at the turbines of the wind farm. It can be seen that the DEL is reduced at all wind turbines in operation with the MPO dispatch, on average by 33%. A reason for the reduction of fatigue loads is the lower variability of turbine power output. Thus, the MPO-based
dispatch could reduce fatigue loads in the absolute power constraint mode.

To reduce the variability of turbine power and thus potentially the DEL in operation with the proportional dispatch, the sampling frequency of the dispatch could be lowered. Reducing the sampling frequency is however expected to result in a lower accuracy in tracking the reference for the total power of the wind farm. Thus a trade-off between tracking accuracy and fatigue loads is necessary. In order to reduce the impact on fatigue loads, the sampling time of dispatch functions is set to 30s in the remaining studies on power control of this work.

4.2.4 Case Study: Large-scale Wind Farm

The performance of the MPO-based dispatch is compared to the other dispatch functions in a simulation case study of a large scale wind farm. The aim is to demonstrate the performance of the MPO-based dispatch in a demanding scenario. As such, the use of a large-scale wind farm results in larger computational costs and increased complexity in the wind farm modelling and the MPO. Moreover, the wind farm is operated in delta-control mode used for secondary regulation, which results in a demanding total power reference, since the reference is closely below the total available power of the wind farm. The results of the case study show an improved tracking of the total power reference when using the MPO-based dispatch.

The case study is structured into the simulation set-up, that is the wind farm, the simulation environment and the wind farm operation mode, and the simulation results, that is the performance of the DFP and the dispatch functions, and the computation time of the MPO.

Simulation Set-up

The simulation set-up describes the wind farm, the simulation environment and the wind farm operation mode used in the large-scale wind farm. The investigated, large-scale wind farm is generic, in order to avoid the association of the presented results with the operation of a particular, real wind farm. Nonetheless, the chosen layout and turbine model shall represent the operation of typical offshore wind farms [88]. Figure 4-20 shows the layout of the wind farm. The spacing of the wind turbines is five rotor diameters between both rows and columns of the square-grid wind farm layout. The wind farm comprises 80 NREL 5MW wind turbines [56] with a rotor diameter of 126m and a rated wind speed of 11.4m/s.

The investigated, large-scale wind farm is simulated using the dynamic simulation framework SWF [55]. More information on the simulation model can be found in section 4.1.2 on the DFP. All simulations use the same wind conditions, that is a mean wind speed of 8m/s and a turbulence intensity of 6%. The wind direction is aligned with the turbine rows as indicated in Figure 4-20. The simulation duration is 5000s, while the discussion of simulation results focuses on the operation from 1000s onward. In the first 1000s the wake flow is building up and thus this time span is not considered.
Figure 4-20: Layout of simulated, generic 80 turbine wind farm used to compare dispatch functions of power controller. Source: [J1]

In the analysis.

In order to provide secondary regulation services, the wind farm is operated in the delta-control mode [14, 87] that is downregulation of the total wind farm power by a certain percentage. Thereby, the wind farm can provide secondary regulation by increasing the farm power output from the downregulated power level to the maximum power output. The total power reference signal $P_{ref}(t)$, as shown in Figure 4-21, is thus defined as

$$P_{ref}(t) = [1 - \gamma]P_{avail, avg}$$  \hspace{1cm} (4.37)

where $\gamma$ is the amount of derating and $P_{avail, avg}$ the backward-averaged total available power prior to the initiation of the control at time $t$. The averaging durations used in the present work are 1min and 5min. The longer averaging duration results in less high frequency content in the reference signal, but a larger time shift of the reference signal into the future as compared to the available power. The derating $\gamma$ is set to 4%.

**Results & Discussion**

The analysis of the case study results is focused on the accuracy of the [DFP], the effect of the investigated dispatch functions on the tracking of the reference for the total power of the wind farm, and the computational speed of the [MPO].

**Dynamic Flow Predictor Performance** The performance of the [MPO]-based dispatch relies on the accuracy of the employed model, that is the [DFP]. The accuracy of the [DFP] is therefore investigated during the operation of the large-scale wind farm.
with the MPO-based dispatch in the same conditions as used in the comparison of the dispatch functions in the following. Figure 4-22 shows the mean and normalized RMS error of wind speed estimates. The error is the difference between the estimate by the DFP and SWT. It can be observed that the mean error increases with downstream turbines from no error to a maximum of 3.6% from the most upstream turbine to the most downstream turbine. Furthermore, the results show that the trend is the same for all turbine rows. The positive bias in the wind speed estimate results in an overestimation of the available turbine power, which is used as a constraint in the MPO-based dispatch. As a result, the power set-points derived by the MPO-based dispatch are more likely to exceed the available power at further downstream turbines. The normalized RMS error of wind speed estimates increases with downstream turbines from 1.6% to a maximum of 5.4%. The persistence-based prediction at upstream turbines ranges between 5.4% and 6.6%. The model-based estimate at downstream turbines is thus more accurate than the persistence-based estimate at upstream turbines. More details on this phenomenon can be found in [J3].

**Performance of MPO**  The use of the MPO-based dispatch is observed to improve the reference tracking during the operation in delta-control mode. The approach could therefore be used to enhance the quality of secondary regulation services. The effect of the dispatch function on the tracking of the total power reference of the delta-control mode is discussed in more detail in the following.

Figure 4-23 shows the effect of the dispatch function on the time-resolved tracking of the total power reference. Overall, it can be observed that the tracking performance is the most accurate with the MPO-based dispatch, and the static dispatch performs worst. Figure 4-23a shows the time series of the total power of the wind farm for operation with the MPO-based dispatch function. It can be observed that the reference is followed well, overall, and the farm power output tends to be below the reference
signal. The use of the reference signal based on the 5-min averaged available power results in a worse tracking performance as compared to the reference based on the 1-min averaged available power. The worse tracking performance is observed in periods when the reference is decreasing, such as, for example, from 2000s to 2500s. In such periods, the larger, negative phase shift in the reference signal introduced by the longer, 5min backward-averaging of the available power results in a more demanding reference signal, as can be seen in Figure 4-21.

Figure 4-23b shows the time series of the total power of the wind farm for operation with the proportional dispatch function. The reference tracking behaviour is similar to the operation with the MPO-based dispatch function. However, a larger variation of the total power and a lower mean total power is observed. Figure 4-23c shows the time series of the total power of the wind farm for operation with the static dispatch function. It can be observed that the tracking is worse that with the other, two dispatch functions. With the static dispatch, the wind farm is only able to deliver the power requested by the reference at few time instances. This is because the demanded total power is distributed equally to the wind turbines, and thus some wind turbines are requested to produce more power than their available power. As a result, there is a steady state error from the total power reference as discussed in Section 4.2.2 on controller tuning.

The tracking error from the total power reference is quantified in Figure 4-24 and Figure 4-25 in terms of the mean error and the NRMS error, respectively. It can be observed that operation with the reference based on shorter averaging of 1min reduces the errors of the MPO-based dispatch and proportional dispatch by 30% and 14%, respectively. There is no effect observed for the static dispatch, since the total power reference is above the farm power output independent of the averaging duration used for the generation of the reference signal. The results therefore show that a shorter averaging duration, employed for the generation of the reference signal used in the delta-control mode, can result in a lower reference following error. The following discussion thus focuses on the results for the reference based on 1min averaging. The lowest error is observed with the MPO-based dispatch function, which shows a mean error of -0.8MW and a NRMS error of 1.5%. The reduction of the mean error with respect to the propor-
Figure 4-23: Effect of dispatch function on tracking of total power reference in simulation of 80-turbine wind farm. Wind farm controller distributes demanded total power using (a,b) MPO-based dispatch function, (c,d) proportional dispatch function and (e,f) static dispatch function. The reference signal is obtained based on 1-min averaged total available power (left column) or 5-min averaged total available power (right column).

Source: [J1]

The improvement in the tracking of the reference for the total power of the wind farm is mainly due to three reasons. First, the DFP provides a more accurate prediction of the available power at wind turbine than the persistence-based prediction used in the proportional dispatch. The performance improvement achieved with the MPO dispatch is likely to be lower in the real wind farm, because of a lower accuracy of the DFP. On the other hand, advances of the DFP such as the automatic correction of the mean prediction error could improve the performance of the MPO dispatch further. Second and third, in the tuning of the MPO dispatch it was observed that the use of a prediction horizon and the penalization of turbine power variation increases the power tracking accuracy.
Figure 4-24: Effect of dispatch function on mean error from total power reference in simulation of 80 turbine wind farm. Source: [J1]

Figure 4-25: Effect of dispatch function on NRMS error of total power reference in simulation of 80 turbine wind farm. Source: [J1]

**MPO Computation Time**  The computation time of the MPO is two orders of magnitude faster than comparable model predictive controllers in literature. A smaller computation time is beneficial as it results in a reduced delay in applying the optimized turbine power distribution to the wind turbines. The computation time of the MPO-based dispatch is on average 0.68s, which is composed of 0.27s for the optimization and 0.41s for the model update. The computation time is calculated on a standard personal computer for the current MATLAB implementation of the MPO-based dispatch. Optimizing the implementation in terms of employed hardware and software can further reduce the computation time. In [20] a comparable, however, nonlinear model-predictive controller is applied to a 80 turbine wind farm for active power control. The computation time of the non-linear optimization is quantified as 60s, that is two orders of magnitude larger than the computation time of the present work.
4.2.5 Summary

This section presents the MPO-based dispatch function for power control of wind farms during ancillary services. The commonly employed proportional dispatch is simple and robust, but only considers the availability of aerodynamic power at wind turbines for distributing the total, requested power to the wind turbines. The use of an optimization-based dispatch function allows to decide on the distribution of total power based on multiple objectives, models of wind farm operation and possible, future trajectories of operation. The proposed MPO-based dispatch function, as such, uses model-predictive, multi-objective optimization. The optimization objectives are to follow a reference for the total power of the wind farm and to penalize variations of turbine power. The employed model is the DFP, which uses a Kalman filter-driven feedback to correct the wind farm flow model dynamically.

The developed MPO-based dispatch function is compared in dynamic simulation to dispatch functions commonly employed in present wind farms in two case studies. In the absolute power constraint mode, the comparison shows that the MPO-based dispatch reduces power variability and fatigue loads by 53% and 33%, respectively. It is further concluded that the sampling frequency of the dispatch function can be used for the trade-off between the accuracy in tracking the power reference and the fatigue loads of wind turbines. The next case study is carried out on an eighty-turbine, large-scale wind farm. It is therefore shown that the MPO dispatch is scalable to large wind farms. The MPO dispatch yields a reduction of the mean error and the NRMS error by 43% and 36% with respect to the proportional dispatch function. Another achievement is the speed of the MPO of only 0.21s for a large-scale wind farm, that is two orders of magnitude faster than for comparable approaches in literature. A response time within 1s provides enough bandwidth to execute other required services of secondary power system regulation like voltage and frequency control.
4.3 Mitigating Turbine Fatigue Loads

Cumulative operations and maintenance (O&M) costs of offshore wind farms can amount to 38% of lifetime costs. In wind farms, upstream turbine wakes can result in up to 80% higher fatigue loads at downstream wind turbines. The present work therefore investigates to reduce wind turbine fatigue loads during the provision of grid balancing services using model predictive wind farm control. The main objective of the developed controller is to follow a total wind farm power reference and to reduce the damage equivalent tower bending moments of the turbines in the wind farm. The control approach uses the DFP to model the dynamics of wind farm operation, and a newly developed model of turbine fatigue loads. The MPC is compared with commonly used wind farm control approaches in two wind farm case studies using a dynamic wind farm simulation tool. The simulation results suggest that the proposed MPC can reduce the sum of the equivalent tower bending moments of wind turbines in a wind farm during provision of ancillary services. Simulations of an eight turbine array show up to 28% lower sum equivalent tower moments as compared to commonly used wind farm controllers. The observed reduction in turbine fatigue loads is attributed to the use of adequate wind farm-scale wind turbine fatigue load models.

Section 4.3 is based on publication [J4].

4.3.1 Introduction

Cumulative O&M costs of an offshore wind farm can amount to 38% of lifetime costs [89]. These wind farm O&M costs are to some degree a function of wind turbine fatigue loads. In wind farms, upstream turbine wakes can result in up to 80% higher fatigue loads at downstream wind turbines [88]. Therefore the mitigation of wind turbine wake-induced fatigue loads is of importance. Existing studies [17, 18, 90, 91] have investigated the reduction of wind turbine fatigue loads during the provision of ancillary services using model predictive wind farm control. However, the investigated approaches use controller objective functions and wind farm operation models, that are not useful for achieving a reduction of turbine fatigue loading in a real wind farm. The proposed objective functions are typically a combination of squared turbine bending moments and the deviation of wind farm power from the reference. Fatigue damage, however, depends on the number of cycles, in addition to their amplitude, and damage accumulates with an exponent that is much higher than the square. It is therefore suggested to use measures of fatigue based on cycle counts, such as damage-equivalent bending moments, in the objective function.

Impediments to controller models lie in the modelling approach and computational costs. For wind farm flow modelling, some approaches [90, 91] do not include a model for the aerodynamic interaction of wind turbines. As mentioned earlier, wake-induced fatigue loads are a major source of wind turbine fatigue loads. It is therefore beneficial to include the effects of wake interaction in the controller model. For this purpose 2D CFD flow models [17, 92] are investigated, which estimate the hub height flow field in a wind farm. An impediment, however, to the use of such models for the control of large scale wind farms is computational cost due to the amount of states used by these CFD models.
The present work investigates the performance of a newly developed MPC which employs the DFP and a statistical turbine fatigue model to estimate wind farm operation. Even though, the developed controller could also be employed as an optimization-based dispatch function, as described in section 4.2, such approach is not chosen in order to simplify analysis. To benchmark the MPC, its performance is compared to standard power controllers for wind farms.

Next, the methodology is detailed. Thereafter, the performance of the developed model predictive wind farm controller is compared to reference tools. The section concludes with the key findings.

4.3.2 Methods

The newly developed model-predictive controller and the simulation environment are discussed in the following.

Model-predictive Controller

The objective of the MPC is to follow the reference for the total power of the wind farm while reducing the mechanical loads of the wind turbines in the wind farm. This is achieved in the cost function of the MPC. The cost function penalizes the deviation of the total power of the wind farm from its reference, the fatigue loads of wind turbines, and the variation of turbine thrust force. The control actions of the MPC are set to be constrained by the availability of aerodynamic power at the wind turbines in the wind farm. The MPC predicts the effect of the control actions on the performance of the wind farm using the DFP and a statistical and deterministic mechanical load model. More information on the DFP model can be found in section 4.1 above and in [J3].

Wind turbine fatigue loads are estimated in the MPC using a newly developed, statistical turbine fatigue load model. The model is a database of damage equivalent, fore-aft turbine tower bending moments in a range of relevant turbine operational conditions. At present, the database covers wind speeds ranging from 5m/s to 8m/s, and turbulence intensities ranging from 6% to 7.5%. The equivalent moments are obtained from simulations of a two turbine array using the SWF simulation tool. Figure 4-26 shows the layout of the two turbine array. The rainfall counting algorithm [93] is used to derive damage equivalent moments from the simulated dynamics of tower bending moments. In the rainfall counting algorithm a Wohler exponent of 4 is used, which is representative of steel. Figure 4-27 shows key results from the database of the turbine fatigue load model for the wind condition relevant for the simulation case.

Standard Power Controllers

The MPC is compared to power controllers commonly employed in current wind farms. This is the feedback PI controller with static or proportional dispatch function, as in-
Figure 4-26: Layout of two turbine array aligned with wind direction. Source: [J4]

introduced in section 4.2.2 on the model-optimized dispatch for power control of wind farms.

Simulation Environment: SimWindFarm

The comparison of the MPC to standard power controllers is conducted in the dynamic simulation framework SWF [55]. More information on the simulation model can be found in section 4.1.2 on the DFP. The simulations use the same wind conditions and a turbine spacing of 4.3D. The simulated wind conditions are a mean wind speed of 8m/s, a turbulence intensity of 6% and a constant wind direction along the turbine row.

4.3.3 Results & Discussion

In the following, first the turbine fatigue load model that is employed in the MPC is investigated. Thereafter, the performance of the MPC is compared to standard power control approaches in two case studies, a two turbine study and an eight turbine study. The conducted studies on the developed MPC show a significant reduction of turbine fatigue loads when compared to standard power control approaches.

Turbine Fatigue Load Model

The developed turbine fatigue load model is a database of turbine fatigue loads of a two turbine array, with a layout as shown in Figure 4-26, for a range of operational conditions and wind conditions. Figure 4-27 shows the effect of turbine operation on the sum of the simulated tower equivalent bending moments of the two turbine array for a single, freestream wind condition. The equivalent moments are derived for turbine power set-points ranging between zero and the available power of the upstream turbine No. 1.

As expected, an increase in a turbine’s power output results in a larger tower bending moment of the same turbine. For the sum of the two turbines’ equivalent tower bending moment the total load minimizing power set-point distribution depends on the value of the total power reference. For a total power reference below 75% of the available
power at turbine No. 1, the lowest sum equivalent moment is observed if the power set-point of both turbines is similar. Thus for a given reference total power, distributing the demanded reference total power to the turbines equally results in the lowest sum equivalent moment in this model. For a total power reference above 75% of the available power at turbine No. 1, the lowest sum equivalent moment is not achieved for an equal distribution of power set-points. Rather, the lowest sum equivalent moment is observed for the largest reduction of the upstream turbine power set-point possible, whilst operating the downstream turbine at maximum power and delivering the demanded total reference power.

Case Study: Two-turbine Array

The two turbine case study evaluates the performance of the developed MPC on a two turbine array during the ancillary service "balance control".

Simulation Set-up

The performance of the MPC is compared with the feedback PI-controller in SWF-simulations of the two turbine array with a layout as shown in Figure 4-26. The PI-controller uses the proportional dispatch and static distribution dispatch functions. The choice of the static distribution shall mimic a wind farm operators desire to reduce wake loads on a downstream turbine. Thus, the static distribution is set to \( \{ f_1 = 0.2; f_2 = 0.8 \} \).

In the "absolute power constraint" mode [87] the wind farm is requested to produce a fixed amount of total power. Figure 4-28 shows the relation of the available total power of the wind farm and the reference signal for the total power during the chosen balancing control. It can be observed that the requested power is set to be less than the wind farm’s available power throughout the entire simulated period. The magnitude of downregulation is less than 75% of the available power at the upstream turbine. Thus,
according to the fatigue load model presented in sub-section 4.3.3, an equal distribution of turbine power set-points results in the lowest sum of turbine fatigue loads.

Figure 4-28: Relation of total available power of wind farm and power reference of wind farm during chosen balancing control scenario. Source: [J4]

**Results** Figure 4-29 shows the variation of turbine power as set by the wind farm controllers. During operation with the PI wind farm controller with static dispatch, the turbine powers stay constant. With the proportional dispatch function, the largest variation in turbine powers is observed. The MPC operates the turbines close to the optimum power set-point derived using the statistical turbine fatigue load model, that is an equal distribution. The variation of turbine power set-points by the MPC aims to reduce the variation of turbine thrust force.

Figure 4-29: Dispatch of total, demanded power to the two-turbine array. Source: [J4]

The simulated total wind farm power is shown in Figure 4-30. It can be observed that for all, tested wind farm controllers the deviations from the power reference are within the Danish grid code limits [87]. With the PI controller the normalized root mean square deviation from the power reference is 0.0083%. The normalized root mean square deviation during operation with the MPC is 2.3%. The deviation from the power reference is larger during operation with the MPC since the MPC objective function
trades off between power reference deviation and mechanical load reduction. The use of the model-optimized dispatch function in combination with a closed-loop feedback controller, as introduced in section 4.2, can reduce the reference following error of the MPC further.

Figure 4-30: Wind farm controller performance in terms of power reference following ability. Source: [J4]

Figure 4-31 shows the effect of the wind farm control approach on the tower bending moments of the turbines of the two turbine array. It can be observed that the bending moments during operation with the MPC are on average 16% smaller as compared to the proportional dispatch approach. The proportional dispatch shows larger equivalent moments mainly due to the larger variations of turbine power. The larger variations of power result in more fluctuations of a turbine’s thrust force, and thus increase the turbine tower fatigue loads. During operation with the static dispatch approach the upstream turbine No. 1 shows 18% smaller fatigue loads than with the MPC. The downstream turbine No. 2, however, shows 85% larger fatigue loads than with the MPC. Thus, the sum fatigue loads of the two turbine array are smaller with the MPC than with the static dispatch.

Figure 4-32 shows the impact of the wind farm control approach on the sum equivalent tower bending moment of the two turbine array. Operation with the MPC shows the smallest, total, equivalent moment, which is 28% lower than under operation with the static dispatch approach and 16% smaller than under operation with the proportional dispatch approach. The developed MPC approach therefore successfully reduces turbine mechanical loads in this case study.

Case Study: Eight-Turbine Array

This case study aims at comparing the controllers on an eight-turbine array during the "absolute power constraint" mode [87]. An eight-turbine array is chosen since it is representative of a streamwise section of a typical offshore wind farm. Thus, the simulation results obtained for the eight-turbine array are expected to be transferable to a
full-scale offshore wind farm. The chosen "balance control" scenario is the same as in the two-turbine case study. As such the ratio of the power reference value to the nominal power of the wind farm is the same. The eight-turbine case study employs the feedback \([PH]\) controller with the proportional dispatch and static distribution dispatch functions. The static distribution is set for this case study as \(\{f_1 = 0.22; f_2 = 0.19; f_3 = 0.17; f_4 = 0.14; f_5 = 0.11; f_6 = 0.08; f_7 = 0.06; f_8 = 0.03\}\). The choice of the distribution mimics a wind farm operators desire to manually dispatch turbines similar to their available power. It is close to the the available power in the nominal operation case, see \[4-33\] but slightly off, though without significant consequence for the purpose of this study, and exactly what wind farms operators would select as distribution factors is anyhow a guesstimate. The \textbf{MPC} targets a dispatch close to an equal distribution of turbine power set-points, as was used for the two-turbine array. Since the turbine fatigue load model is derived for a two-turbine array, it is however not given that an equal set-point distribution results in the lowest, possible fatigue loads for an

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**Figure 4-31:** Effect of wind farm control approach on simulated, equivalent tower bending moment of turbines in two turbine array. Source: [J4]

**Figure 4-32:** Impact of control approach on total wind farm fatigue loads. Source: [J4]
Figure 4-33: Distribution of turbine power in nominal operation. Turbine powers are normalized by power of upstream turbine. Source: [J4]

The eight-turbine array.

Figure 4-34 shows the effect of the wind farm control approach on the tower bending moment of the turbines of the eight-turbine array. It can be observed that the equivalent moments of the first, six upstream turbines increase with each successive downstream turbine due to larger turbulence intensity downstream. Under operation with the MPC, these six upstream turbines experience the lowest equivalent tower bending moment.

Figure 4-34: Effect of wind farm control approach on simulated, equivalent tower bending moment of turbines in eight turbine array. Source: [J4]

The lowest sum equivalent moments of all turbines are observed under operation with the MPC as can be seen in Figure 4-35. Under operation with the MPC the sum equivalent moments are 25% lower than under operation with the static dispatch and are 22% lower than under operation with the proportional dispatch.
Main Findings

The results of the case studies show that in the PI-controller the lack of knowledge on the effect of the power set-point distribution on turbine fatigue loads can result in less beneficial wind farm operation. In the present work such lack of knowledge of a wind farm operator results in up to 28% larger sum equivalent tower bending moments. The two case studies show that the model predictive wind farm control approach can reduce the sum equivalent tower bending moment as compared to commonly used wind farm control approaches. Moreover, the predictive nature of the MPC allows it to consider the future evolution of the wind speed at the turbines when deciding the most beneficial, future control actions. As such the controller takes the future available power at the wind turbines into account.

4.3.4 Summary

The results of this section demonstrate how model-based wind farm control can reduce the sum of the equivalent tower bending moments of wind turbines in a wind farm during operation in "absolute power constraint" mode. Simulations of an eight-turbine array show up to 28% lower sum equivalent tower moments during operation with the developed model-predictive controller. Commonly used wind farm controllers lack knowledge of the effect of turbine operation on wind turbine fatigue loads. The observed 28% reduction of fatigue loads stems from the use of such knowledge in the developed model-predictive controller. Future work should focus on the development of fatigue load models from higher fidelity aeroelastic simulation tools, and further analysis of the MPC.
Chapter 5

Induction-Control: Optimizing Nominal Operation

In wind farms, the aerodynamic interaction of wind turbines through wakes causes power loss and increased fatigue loads. To mitigate these adverse effects, it is investigated in literature to offset the blade pitch angle at upstream turbines in order to thereby weaken the wake. In the current study, large-eddy simulations provide the first, high fidelity evidence on the impact of the approach on fatigue loads. It is observed that a positive offset of pitch angle yields a beneficial reduction of the sum fatigue loads of a two-turbine array. Derating the upstream turbine by 7.0% results in a reduction of damage-equivalent loads on the downstream turbine of 12% in the blade root, of 7.4% in the tilt, and of 7.4% in the yaw. The approach therefore allows for the trade-off between power production and fatigue loads in nominal wind farm operation. Using the approach to increase total power production has yielded mixed outcomes in literature. It is however unclear if the investigations were conducted in the most beneficial conditions. Therefore, in this work, a wide range of external conditions is analyzed. The dynamic wake meandering model (DWM) and Larsen wake model show the largest, potential power gain in low turbulence intensity and turbine spacing, and a wind direction aligned with the wind turbines. Even in these potentially most beneficial conditions, large-eddy simulations show reduced total power production when using an offset of the pitch angle at the upstream turbine of a two-turbine array. It is therefore uncertain if the approach could increase total power.

The LES have been performed by Søren Juhl Andersen, who provided the raw output data. He is gratefully acknowledged for making the data available.

5.1 Introduction

To leverage economies-of-scale, wind turbines are typically clustered in wind farms. The resulting interaction of wind turbine wakes with downstream turbines causes power loss of up to 40% and up to 80% larger fatigue loads [6]. Given the global capacity of wind power of 539,123MW in 2017 [3], the mitigation of the adverse impact of wakes
in wind farms is of interest. Generally, approaches for the mitigation of wake effects are investigated with respect to the design and control of wind turbines and wind farms.

An advantage of reducing wake effects using control is the applicability to existing wind farms. In research on turbine control, the modification of the downregulation strategy is investigated to reduce wake effects at downstream turbines [13, 94]. In wind farm control, the approach is to mitigate wake effects by coordinating the operation of wind turbines. Approaches of wind farm control can be categorized according to the mode of wind farm operation, that is (i) nominal operation or (ii) downregulated operation. In downregulated operation, the objective is to control the total power output of the wind farm as to follow a reference signal. An additional, optional objective is to simultaneously reduce the fatigue loads on the wind turbines in the wind farm. Such wind farm control is typically referred to as power control. The accurate tracking of the reference for the total power of the wind farm is achieved by the use of a closed-loop feedback controller [14]. The total power demanded from the wind farm by the feedback controller is distributed to the wind turbines using a dispatch function [15].

In nominal operation, the objective is to maximize the total power of the wind farm. The optimization approach is usually based on the hypothesis that some non-optimum operating condition of wind turbines increases total power production. As such, manually induced yaw misalignment at upstream turbines is investigated in numerical [30, 31] and experimental [32, 33] studies with the objective to shift the wake flow laterally and thereby increase the power of downstream turbines. Another approach is the use of a positive offset of the blade pitch angle at the upstream turbine so that turbines downstream benefit from higher wind speeds in the weakened wake. This approach is termed induction-control in this paper. An increase in total power production can be observed in simulations that are based on an actuator disc wind turbine model [34] or semi-empirical wake models [36]. Such models however simplify the aerodynamic interaction between wind turbines, in particular for multiple wake cases. This results in an error between the model-estimated and the actual wind farm performance [39]. It is therefore of interest to investigate the approach in experiments and in higher fidelity simulation tools. In the wind tunnel study by Barth et al. [41] an increase in total power is observed, whilst in the study by Campagnolo et al. [43] no increase is reported. The use of down-scaled models of wind turbines in wind tunnel tests results in a lower Reynolds number as compared to the full-scale, and as a result in differences of the turbine performance [44]. A wind farm control strategy developed in a wind tunnel will thus be different from the full scale. A full-scale experiment [45] observed an increase of the total power. Mixed outcomes on the benefit of the approach are also reported in higher fidelity simulation studies. A CFD study based on RANS reports an increase in total power [46]. A decrease in total power is reported in a study based on LES [47].

However, the experimental and high fidelity, numerical investigations in literature were conducted in certain conditions, only. It is thus unclear if the investigations were conducted in the most beneficial conditions. Therefore, in this work, a wide range of external conditions is analyzed, that is turbine spacing and atmospheric conditions comprising wind speed, wind direction, and turbulence intensity. Thereafter, the observed, potentially most beneficial condition is analyzed using the LES tool EllipSys3D. The simulations provide a trustworthy insight into the effect of induction-control on the
total power production. Furthermore, this work is the first to give high fidelity evidence on the impact of induction-control on the fatigue loads of wind turbines in nominal operation.

The structure of this chapter is as follows. In section 2, the methodology is detailed. In section 3, first, the impact of environmental conditions on total power is investigated, and thereafter, the potentially most beneficial condition is analyzed using LES simulation. Section 4 concludes with a summary of the key findings.

5.2 Methods

The approach of the present work for the calculation of induction-control strategies, that aim to maximize the total power of the wind farm, is discussed in the following. Thereafter, the EllipSys3D solver is outlined, which is used to perform the large-eddy simulations.

5.2.1 Maximization of Wind Farm Power

Optimized induction-control strategies are determined in the present work using model-based, numerical optimization. The employed optimization algorithm is heuristic. The objective function, a novel algorithm to split the optimization domain, and the utilized models of wind farm operation are described in the following.

Available Optimization Algorithms

Figure 5-1 shows the developed solutions for power-maximizing wind farm control of the DTU Wind Farm Controller framework [C5]. The objective function used by the wind farm controller can aim to either (i) maximize the total wind farm power or (ii) to maximize each individual turbine’s power. The design of a wind farm controller for the latter objective is simple, as it requires to request the maximum power output from each individual turbine. For the former objective, that is the maximization of the total wind farm power, the control approaches differ depending on whether the optimization is performed online or offline. For online optimization a model-based or a model-free, Bayesian approach can be used.

The model-based total power maximization problem (Eq. 5.3), is solved using heuristic, gradient-free optimization techniques, while modelling wind farm operation using either the sDWM model or the sPossPOW model. The model-free Bayesian approach is presented in [53], but not discussed in more detail since the work is not part of this thesis. In addition to the online optimization approaches, the operation strategy that shall maximize the total power of the wind farm can be obtained from a look-up table. The table is generated offline using, for example, the model-based optimization solution used for the online optimization procedure.
Objective Function

The objective, to maximize the total power production of a wind farm using induction-control, translates into the following cost function $\Psi$

$$\Psi(\gamma, t) = \int_{t}^{t+T_{\text{oper}}} \sum_{j=1}^{J} P_{j}(t', \gamma_j(t')) dt'$$  \hspace{1cm} (5.1)

where $t$ is the time and $\gamma$ is the deratings of the wind turbines over the duration of the normal operation $T_{\text{oper}}$, $J$ is the number of wind turbines in the wind farm. $P_{j}(t', \gamma_j(t'))$ is the power of turbine $j$ at time $t'$ and derating $\gamma_j(t')$. The derating is defined as $\gamma = P/P_{PC}$ that is the ratio of the turbine’s power output $P$ to the turbine’s maximum available power $P_{PC}$ at the current wind speed. The use of such objective function is investigated in a few studies [23, 95]. However, the duration of the optimization is in the order of 100s in these studies. Although remarkably fast given the problem’s complexity, this results in a delay in the implementation of the optimized deratings to the wind turbines.

The duration can be reduced by not optimizing over time in the cost function. Instead, the objective is to maximize the extraction of kinetic energy from the ensemble-averaged flow passing through the wind farm. The objective is thus to maximize the time-shifted, ensemble-averaged total power of the wind farm as

$$\Psi(\tilde{\gamma}, t) = \langle P_{\text{tot}}(\tilde{\gamma}, t) \rangle_{ABL, \Delta t} = \left\langle \sum_{j=1}^{J} P_{j}(t + \Delta t_j, \gamma_j) \right\rangle_{ABL}$$  \hspace{1cm} (5.2)

where $\langle P_{\text{tot}}(\tilde{\gamma}, t) \rangle_{\Delta t}$ is the ensemble-averaged, time-shifted sum power of the turbines in the wind farm at time $t$ and deratings $\tilde{\gamma}$ of the wind turbines. $\Delta t_j$ is the duration of the
propagation of flow from the most upstream turbine to turbine \( j \). The ensemble average is defined as the ensemble of flow realizations that have the same atmospheric boundary layer (ABL) stability and 10min-averaged, freestream wind direction and wind speed. Eq. [5.2] can be solved using a model of the stationary wind farm operation and the following objective function

\[
\Psi(\bar{\gamma})_{ABL} = \langle P_{tot}(\bar{\gamma}) \rangle_{ABL} = \sum_{j=1}^{J} \langle P_j(\gamma_j) \rangle_{ABL} \tag{5.3}
\]

**Domain Split Algorithm**

In order to increase the computational effectiveness of the total power maximization problem, that is particularly useful for large-scale wind farms, the optimization domain is split into sub-domains based on wind turbine wake interactions, as illustrated in Figure 5-2. A pair of turbines is defined to be interacting aerodynamically, if there is an overlap of the upstream turbine’s wake with the downstream turbine rotor area. The width of the wake is calculated using the wake models employed in sDWM and sPossPOW.

![Figure 5-2: Determination of optimization sub-domains based on aerodynamic interaction of wind turbines. Shown are a colorplot of hub height axial wind speed simulated by SWF, the wind turbines denoted by black bars, and the aerodynamic interaction of wind turbines depicted by lines connecting the turbines.](image)

The domain is split using a newly developed recursive graph theory algorithm, as described in algorithm [I]. The algorithm loops over all turbines in the wind farm in the order of the direction of wind flow. For each turbine, the recursive DeepSearch function is used to determine graphs of turbines connected to the turbine through wake interaction. Throughout the process, graphs of interconnected turbines are created. Finally, the optimization problem can be performed for each of these graphs independently.
**Data:** $T$: set of turbines ordered in wind flow direction 
$ID$: turbine ID 
$T(ID)$: set of turbines downstream of turbine $ID$ 
$IDD$: $ID \in T(ID)$ 
$newgraph$: graph object to which new turbines are added to by DeepSearch function 
$graphs$: set of graphs build by DeepSearch function

```
begin
  graphs = {}
  for ID ∈ T do
    Initialize newgraph as empty graph.
    DeepSearch (newgraph, graphs, ID)
    if newgraph ≠ {} then
      Add newgraph to graphs.
    end
  end
end
```

Function DeepSearch (newgraph, graphs, ID):
```
if ID ∈ graphs then
  | Merge graph in graphs that contains turbine ID with newgraph.
else
  if newgraph = {} AND ID ∉ newgraph then
    Add ID to newgraph.
    if $T(ID)$ ≠ {} then
      for IDD ∈ $T(ID)$ do
        if IDD ∉ newgraph then
          DeepSearch (newgraph, graphs, IDD)
        end
      end
    end
  end
end
```

**Algorithm 1:** Domain split

**Wind Farm Models**

The wind farm operation models sDWM and sPossPOW are used to quantify the value of the objective function (Eq. 5.3) of the power maximization problem. Both models employ the same downregulation strategy to characterize turbine operation.

**Downregulation Strategy** The downregulation strategy of a wind turbine defines the impact of derating the turbine on its wake characteristics [94]. To derate a wind turbine it requires the turbine controller to reduce the aerodynamic power of the rotor. This is achieved by changing the rotational speed of the rotor and / or the blade pitch angle. The coordinated change of these two operational variables by the turbine controller with the
objective to adjust aerodynamic power is termed downregulation strategy. In the present work, the approach of the downregulation strategy is to keep the torque-speed relation of a standard turbine controller \[54\] and to use a positive offset of the blade pitch angle to adjust rotor aerodynamic power. More details on other downregulation strategies can be found in \[38\].

The impact of the downregulation strategy on wake flow is due to the difference in the aerodynamic effect of changes in blade pitch angle and rotor rotational speed. The same level of derating can be achieved by different combinations of pitch angle and rotor speed. The coordination of these two variables is defined by the downregulation strategy and as a result, the downregulation strategy defines the effect of derating on wake flow. More details on downregulation strategies and their implementation in the turbine controller is discussed in the ensuing chapter on Integration of Turbine Control Architecture.

**sDWM** The sDWM model \[1\] is based on the DWM \[96\], which was originally created with the objective to simultaneously, dynamically simulate turbine power and mechanical loads. Instead of such dynamic simulation of wind farm operation, the sDWM model is stationary and provides an estimate of the expected wind turbine power in a wind farm. It captures relevant physics for the modelling of wind farm flow, that is turbine specific induction, the evolution of wake deficit and wake turbulence throughout the wind farm, and the effect of atmospheric stability and ambient turbulence on wake flow.

![Figure 5-3: Schematic of process of flow modelling in sDWM model for multiple wind turbines \[1\].](image)

Figure 5-3 shows the iterative, three-step process of flow modelling in the sDWM model. The process iterates through the turbines in the wind farm in the direction of the mean wind direction. For each turbine, it calculates the impact of the turbine’s wake on the flow field downstream. In the first step, the inlet boundary condition for wake flow modelling is determined using the blade-element-momentum (BEM) method. Input to BEM calculations are the wind conditions at the turbine, that is rotor-averaged wind speed, rotor-averaged turbulence intensity and atmospheric stability, and turbine model specifications as used in aeroelastic codes such as HAWC2 \[97\]. In the second step, the statistically-averaged wake deficit is calculated using a modified version of the DWM. As in the original version, wake flow modelling is split into the evolution of the wake
deficit in the meandering frame of reference and the meandering of the wake. Also, the wake deficit in the meandering frame of reference is obtained using the steady-state thin-shear layer approximation of the Navier-Stokes equation proposed by Ainsle [98]. In contrast to the original DWM in the sDWM model, wake meandering is modelled statistically. As such the wake deficit in the meandering frame of reference is convoluted with the Gaussian distribution of the position of the meandering wake center. The result is the time-averaged wake flow field behind the wind turbine, that is the third step. In case of multiple, wake-generating wind turbines, the flow field is obtained using wake superposition methods [99]. The turbulence intensity field in the wake of a wind turbine is determined similarly to the above outlined procedure for wind speed. The turbulence intensity in the meandering frame of reference is as proposed by Keck et al. [100] driven by the shear stress, velocity fluctuations and the ambient turbulence intensity. As for the wind speed model, the turbulence intensity field in the fixed frame of reference is obtained using a convolution with a Gaussian distribution to model the effect of wake meandering.

The wind conditions used as input for modelling a turbine’s wake differ between turbines in freestream and turbines facing wake flow. For a turbine in freestream, the ambient wind conditions are used as input. For a turbine in wake flow, the wind conditions are obtained from the flow field model. The power output of a wind turbine is obtained using the time and rotor-averaged wind speed and the turbine model. More details on the sDWM model, and on results demonstrating the suitability of the modelling approach can be found in [1].

sPossPOW sPossPOW is a modular framework for modelling stationary wind farm operation based on the PossPOW model [72]. The main difference to the PossPOW model is that wind farm operation is considered as stationary in sPossPOW. The sPossPOW framework is structured into a power model and a flow model. The approaches available for the modelling of wind speed and turbulence intensity are shown in Figure 5-4.

![Figure 5-4: Wake models and turbulence intensity models available in modular sPossPOW framework.](image)

Power model The stationary power output $P_j$ of a turbine $j$ is calculated as
\[ \langle P_j(\gamma) \rangle = \frac{1}{2} \rho A c_P(\gamma) \langle u_j^3 \rangle \]  

(5.4)

where \( u_j \) is the rotor-effective wind speed of the turbine. The air density \( \rho \) is modelled to be constant throughout the wind farm.

**Flow model** The flow model consists of a model for each turbine, the evolution of wind speed throughout the wind farm and the development of turbulence intensity within the farm. The evolution of wind speed is modelled as follows. The wind speed at upstream turbines is given by the mean wind speed in free flow. The wind speed at a downstream turbine is calculated as the sum of the superimposed wake deficits from all upstream turbines and the freestream wind speed. Three wake deficit models are available in the sPossPOW framework, that is the Jensen model [86], the recalibrated Larsen model [72], and the Frandsen model [82]. In the present work, the recalibrated Larsen model is used to model wake wind speed. This is because the model was recalibrated to downregulated turbine operation [72] and is thus considered better suited to study induction-control. The wake models provide an estimate of the wake deficit \( \delta u \) from an upstream turbine \( l \) to a downstream turbine \( i \) as

\[
\delta u_{i,l} = f(\Delta x_{i,l}, \Delta y_{i,l}, c_{T,l}(\gamma_l), T I_l) u_l
\]

(5.5)

where \( \Delta x_{i,l} \) is the separation distance of the two turbines, \( \Delta y_{i,l} \) the separation distance in cross-axial flow direction, \( c_{T,l} \) the thrust coefficient of the upstream turbine, and \( T I_l \) and \( u_l \) the turbulence intensity and wind speed at the upstream turbine. The approach for superimposing wake deficits is chosen in accordance to the wake deficit model. To determine if a wake affects a downstream turbine, the overlap of the wake with the rotor of the downstream turbine and the separation distance of these turbines is used. The radius \( R_{wake,l} \) of the wake of a turbine \( l \) is given by the wake deficit models as

\[
R_{wake,l} = g(\Delta x_{i,l}, c_{T,l}, T I_l)
\]

(5.6)

where \( c_{T,l} \) and \( T I_l \) are the thrust coefficient and turbulence intensity at the upstream turbine.

The model of turbulence intensity consists of a model for the ambient turbulence intensity \( T I_{amb} \) and a model for the wake-added turbulence intensity \( \Delta T I \). The estimates of ambient turbulence intensity and wake-added turbulence intensity are used to calculate the turbulence intensity \( T I \) at a wind turbine according to Frandsen [101] as

\[ T I = \sqrt{T I_{amb}^2 + \Delta T I^2} \]

(5.7)

In sPossPOW ambient turbulence intensity can be estimated using real-time measurements or empirical data. The added turbulence intensity can be modelled using either
the Porté-Agel model [60], the Frandsen model [101], or an empirical look-up table. The added turbulence intensity at a downstream turbine \( i \) is calculated in these models as

\[
\Delta TI_{i,l} = h(\Delta x_{i,l}, \Delta y_{i,l}, cT, l, TI_{amb,l}, R_{wake,l})
\]  

(5.8)

5.2.2 EllipSys3D

This section is adapted from [102].

The three-dimensional flow solver EllipSys3D [103,104] is used for the LES simulations. EllipSys3D solves the incompressible Navier-Stokes equations in general curvilinear coordinates, which are discretized in a block-structured approach with a collocated grid arrangement. The pressure correction equation is solved using the PISO algorithm and the Rhie/Chow interpolation technique is used to avoid pressure decoupling. The convective terms are discretized using a combination of the third-order QUICK scheme and the fourth-order central differencing scheme in order to avoid numerical wiggles and reduce numerical diffusion. A low pass filter is applied to the Navier-Stokes equations in a LES framework, which yields a filtered velocity field of resolved large scales in time and space, while scales smaller than the grid scale are modelled through a sub-grid scale (SGS) model, which provides the turbulence closure. The employed SGS model is based on the mixed scale model by Ta Phuoc et al. [105].

Several body forces are explicitly introduced in the numerical domain to represent the effects of the wind turbines, atmospheric turbulence and the ABL. The individual body forces are described in the following.

Wind Turbine Modelling

The wind turbines are modelled using the actuator line method, where body forces are imposed along rotating lines, see Sørensen & Shen [106] and Troldborg for validation [107]. The actuator line method is advantageous as it requires significantly fewer cells than a fully resolved wind turbine to model the influence of the turbine, and still enables detailed studies of the wake dynamics. Furthermore, the actuator line can be used directly in simple structured grids. However, the actuator line method depends on the quality of aerofoil data. In the current implementation, the actuator line is fully coupled to Flex5, an aero-elastic code used to assess the aerodynamic deflections and load responses of wind turbines [108]. The details of the coupling can be found in Sørensen et al. [109]. The simulated wind turbine in the present work is a typical multi-megawatt, offshore wind turbine.

The fully coupled system includes a dynamic controller, which makes the turbine respond to the incoming flow, e.g. changing the blade pitch and hence thrust force applied to the flow. The controller combines a variable speed, proportional controller for below rated winds and a PI pitch angle controller for wind speeds above rated, see Hansen et
al. [110] for details on turbine controllers.

Applying Atmospheric Turbulence

Body forces are also employed to introduce atmospheric turbulence into the flow as described by Gilling et al. [111]. The body forces are obtained from the turbulent fluctuations generated by the Mann model [66, 67]. The Mann model is a linearization of the incompressible Navier-Stokes equations and assumes Taylor’s frozen turbulence hypothesis to generate three-dimensional field of all three velocity components. The advantage of the Mann model is that second-order statistics (variance, cross-spectra, etc.) are matched to those occurring in a neutral atmosphere and the generated turbulence is homogeneous, anisotropic and stationary.

The turbulence is generated in a box of total extent 59520 m x 930 m x 930 m in the streamwise, lateral and vertical directions, which is imposed by body forces in a plane 4.5 rotor radiuses upstream of the first wind turbine.

Atmospheric Boundary Layer

The ABL is also modelled using body forces as described by Mikkelsen et al. [112]. The advantage of using body forces is that only a very short precursor simulation is required to determine the body forces necessary to maintain any boundary layer profile. The body forces are maintained throughout the domain and simulations, i.e. acting similar to a constant pressure gradient. Troldborg et al. [113] assessed the method and found that the committed error is inversely proportional to the Reynolds number, hence insignificant. The current simulations are all conducted with a shear exponent of $\alpha_{PBL} = 0.14$ and the ABL is neutral.

5.3 Impact of Induction-Control

To determine if induction-control based on a positive pitch-offset can increase the total power of a wind farm, the present work investigates the approach in the potentially, most beneficial, external conditions. Therefore, first, the impact of wind conditions and turbine spacing on the maximum, potential power gain of a two turbine array is evaluated using two flow models that is sDWM and sPossPOW. Thereafter, the observed, potentially, most beneficial condition is analyzed on the same turbine array using LES. In addition to power, the LES study also investigates the fatigue loads at wind turbines using an aeroelastic turbine model. The insight on fatigue loads is useful to evaluate the possibility of trading-off power and fatigue of a wind farm using induction-control during nominal operation.
5.3.1 Effect of External Conditions

The following study investigates the effect of external conditions on the impact of induction-control on the power output of a wind farm. The investigated external conditions are ambient, mean wind direction, turbulence intensity, wind speed, and spacing of wind turbines.

Wind Speed Insensitivity

It can be shown that, based on certain considerations, the optimum derating of wind turbines is insensitive to the mean, freestream wind speed. The main consideration is that the wind turbines are operating below rated rotor rotational speed and the down-regulation strategy of the turbine controller is as discussed in section 5.2.1. Given these considerations, the thrust coefficient $c_T$ and power coefficient $c_P$ of nominal operation are typically insensitive to changes in wind speed. This results in the insensitivity of the optimum derating to wind speed.

![Figure 5-5: Layout of two turbine array used for investigation of environmental conditions on induction-driven power gain.](image)

For a two-turbine scenario, as shown in Figure 5-5, this can be demonstrated as follows. For the two-turbine array, the objective function (Eq. 5.3) results as

$$
\Psi(\gamma) = \langle P_1(\gamma_1) \rangle + \langle P_2(\gamma_2) \rangle
$$ (5.9)

The expected turbine power $\langle P(\gamma) \rangle$ can be modelled as

$$
\langle P(\gamma) \rangle = \frac{1}{2} \rho A c_P(\gamma) \langle u^3 \rangle
$$ (5.10)

where $\rho$ is the air density, $A$ the turbine rotor area, and $c_P$ the turbine power coefficient. Next, it is assumed that the aerodynamic interaction of wind turbines can be estimated using an actuator disc model or standard engineering wake model [99]. As a result, the wind speed $u_2$ at downstream turbine no. 2 can be obtained from the wind speed $u_1$ at upstream turbine no. 1 as a function of the derating $\gamma_1$ at the upstream turbine as

$$
u_2 = u_1 f(\gamma_1)
$$ (5.11)
Using Eq. 5.10 and Eq. 5.11 the objective function of the two turbine array (Eq. 5.9) can be written as

\[ \Psi(\vec{\gamma}) = \frac{1}{2} \rho A c_P(\gamma_1)\langle u_1^3 \rangle + \frac{1}{2} \rho A c_P(\gamma_2) f(\gamma_1)^3 \langle u_1^3 \rangle \]
\[ = \frac{1}{2} \rho A \langle u_1^3 \rangle (c_p(\gamma_1) + c_p(\gamma_2) f(\gamma_1)^3) \]  
(5.12)

Hence, the optimum derating \( \vec{\gamma}_{opt} \) is independent of the wind speed at the upstream turbine in the two turbine case. This result can be expanded to wind farms of more than two turbines. The underlying assumption for this is that multiple wake cases are modelled using the maximum deficit wake superpositioning approach [99].

**Turbulence Intensity, Wind Direction and Spacing**

The impact of ambient turbulence intensity, wind direction and turbine spacing on the maximum, potential power gain of a two turbine array are investigated in a parametric study.

**Set-up** For each combination of conditions the optimum derating \( \vec{\gamma} \) and resulting gain in total power is determined. The range of conditions covered by the study is shown in Table 5.1 below.

<table>
<thead>
<tr>
<th></th>
<th>Turbulence intensity</th>
<th>Spacing</th>
<th>Wind direction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimum value</td>
<td>4%</td>
<td>4D</td>
<td>0°</td>
</tr>
<tr>
<td>Maximum value</td>
<td>10%</td>
<td>10D</td>
<td>25°</td>
</tr>
<tr>
<td>Step size</td>
<td>1%</td>
<td>1D</td>
<td>5°</td>
</tr>
</tbody>
</table>

Table 5.1: External conditions investigated in parametric study.

The parametric study is performed using two different models of wind farm operation, that is sDWM and sPossPOW. The models are described in section 5.2.1 above. The sPossPOW model employs for the wake deficit the recalibrated Larsen model and for the added turbulence intensity the Porté-Agel model. The Larsen model was recalibrated for better accuracy in downregulated turbine operation by Göçmen et al. [72]. The model-based optimization is solved using heuristic algorithms. The layout of the two turbine array is shown in Figure 5-5 above. The wind direction is measured relative to the line connecting the two turbines. As such, for a wind direction of 0°, the flow direction is aligned with the turbine row. The wind turbines are modelled as multi-megawatt, offshore wind turbines. More details cannot be disclosed.

**Results & Discussion** Figure 5-6 shows the effect of turbine spacing, turbulence intensity and wind direction on the total power gain predicted by the sDWM and sPossPOW models.
model. The same qualitative impact of the investigated external conditions is observed with sDWM and sPossPOW. With both models the observed trend is an increase of the gain in total power with smaller turbine spacing, lower turbulence intensity and a smaller misalignment between wind direction and turbine array. The effect of external conditions can be explained as follows. With a positive offset of pitch angle, the upstream turbine extracts less power from the flow, and the thrust of the turbine on the flow is reduced. As a result, there is additional kinetic energy in the near wake of the turbine. With increasing downstream distance, this additional energy is, however, increasingly distributed radially, on a time-average. This is because of the expansion of wake flow and the meandering of the wake. Consequently, the rotor of the downstream turbine can only capture a fraction of the additional energy [47].

As a result, with larger turbine spacing the amount of additional kinetic energy that reaches the downstream turbine decreases. Hence, the gain in power observed in the parametric study decreases with larger spacing. Similarly, larger turbulence intensity results in more mixing of the wake flow with the ABL, and thus a stronger radial distribution of the additional kinetic energy. As a result, less of the additional kinetic energy reaches the downstream turbine and the gain in total power is smaller. With regards to wind direction, a larger misalignment between wind direction and turbine array results in less overlap of wake flow with the downstream turbine. Consequently, the gain in total power is smaller with larger misalignment as observed in the parametric study.

The largest gain in total power is observed at the same conditions in sDWM and sPossPOW. That is a turbulence intensity of 4%, a turbine spacing of 4D and a wind direction of 0deg. The maximum gain is 2.0% in sDWM and 1.1% in sPossPOW. These gains are achieved at an optimized derating of 4.0% in sDWM and 1.2% in sPossPOW.

The sensitivity of the power gain to wind direction is similar between sPossPOW and sDWM, as can be seen in Figure 5-6. The sensitivity to turbulence intensity and turbine spacing differs. It can be observed that the power gain in sPossPOW is less sensitive to turbine spacing than in sDWM. On the other hand, sPossPOW is more sensitive to turbulence intensity than sDWM. This difference is due to the different sensitivity of the models in predicting the wake deficit. A larger deficit usually results in a bigger potential gain in power. As a result, a larger sensitivity of the wake deficit results in a bigger sensitivity of the power gain.
Figure 5-6: Effect of turbulence intensity, turbine spacing and wind direction on total power gain of two turbine array. Wind farm operation is modelled using sDWM and sPossPOW.
This is confirmed in the comparison of the sensitivity of the wake deficit between the two models with respect to spacing, turbulence intensity and wind direction, shown in Figure 5-7. The comparison is conducted on the same two-turbine array as the parametric study. The turbine array is considered aligned with the wind direction. In the figures, the rotor effective wind speed at the downstream turbine is normalized with the rotor effective wind speed at the upstream turbine. Each wind turbine is maximizing its individual power output. Figure 5-7.a shows that the wind speed predicted by the recalibrated Larsen model in sPossPOW is less sensitive to changes in downstream distance than in sDWM. On the other hand, it is more sensitive to ambient turbulence intensity than in sDWM, as shown in Figure 5-7.b. It can be observed in 5-7.c that the sensitivity to wind direction is similar between both models. The observations on the sensitivity of wind speed are thus in line with the above discussed sensitivity of the total power gain.

![Figure 5-7: Sensitivity of rotor effective wind speed at downstream turbine to (a) downstream distance, (b) ambient turbulence intensity, and (c) wind direction. In the sensitivity analysis of one condition the other external conditions are constant. The analysis is conducted on the two-turbine array used in the parametric study.](image)

5.3.2 LES Study

The objective of the LES study is to investigate if induction-control can increase total power in a realistic setting, that is comparable to the operation of a real wind farm. The use of LES is considered a suited environment for the study as it allows to model the dynamics of wind turbines and wind farm flow in high fidelity. To investigate if
induction-control can increase total power, the simulation conditions are set to the potentially most beneficial, yet relevant condition, as summarized in Table 5.2. The simulated wind farm is the two-turbine array that is used in section 5.3.1 to investigate the impact of external conditions. The spacing of the turbines is set to 5D, albeit the largest potential gain in power was observed at a spacing of 4D. This is because present offshore wind farms are typically built with spacings of at least 5D.

The ambient wind speed is set to 8m/s, and thus both wind turbines operate below rated rotational speed. As a result, it is expected that the optimum derating is insensitive to the ambient wind speed, as discussed in section 5.3.1. The turbulence intensity and wind direction are set to 4% and 0°, that is the most beneficial condition observed in the parametric study. Hence, the ambient, mean wind direction is aligned with the turbine array. The stability of the ABL is set to the neutral regime, which is characterized using the Mann parameters $\Gamma = 3.2$, $\alpha \varepsilon = 0.01$ and $L = 50m$, according to Sathe et al. [68]. The results based on sDWM are also based on neutral stability. The sPossPOW model does not consider ABL stability.

In the LES, the derating of wind turbines is set in accordance with the results of the parametric study. In the wind conditions and turbine spacing chosen for the LES simulations, the optimized derating determined using sDWM and sPossPOW is 4% and 1.2%, respectively. The derating realized in the LES simulations is 1.8%, 4.4% and 7.0%. There is thus a difference between the derating realized in LES and the optimized values obtained using sDWM and sPossPOW. The difference results from the implicit setting of turbine derating by the use of the blade pitch angle in EllipSys3D.

### Atmospheric conditions

<table>
<thead>
<tr>
<th>Ambient wind speed</th>
<th>Turbulence intensity</th>
<th>Wind direction</th>
<th>$\Gamma$</th>
<th>$\alpha \varepsilon = 0.01$</th>
<th>$L$</th>
</tr>
</thead>
<tbody>
<tr>
<td>8.0m/s</td>
<td>4.0%</td>
<td>0.0°</td>
<td>3.2</td>
<td>50m</td>
<td></td>
</tr>
</tbody>
</table>

### Wind turbine

<table>
<thead>
<tr>
<th>Spacing</th>
<th>Upstream derating</th>
</tr>
</thead>
<tbody>
<tr>
<td>5.0D</td>
<td>0.0%, 1.8%, 4.4%, 7.0%</td>
</tr>
</tbody>
</table>

Table 5.2: Summary of key settings for atmospheric conditions and wind turbines used in LES simulations.

### Power Impact

Figure 5-8 shows the effect of derating on the LES simulated dynamics of power output. Figure 5-8a depicts the power output of the upstream turbine. It can be observed that, as desired, a larger derating effects a bigger reduction of power output throughout the entire simulated time period. The reduced power extraction at the upstream turbine impacts the wind farm flow, and consequently, the operation of the downstream turbine. The derating of the upstream turbine is realized using a positive offset of the pitch angle. This results in a reduction of both the power coefficient and thrust coefficient of the upstream turbine. The lower thrust coefficient can effect an increased wind speed in the turbine’s wake. The increased wind speed can, at times, increase the downstream...
turbine power output, as shown in the following.

Figure 5-8: Effect of derating upstream turbine of two-turbine array on the simulated dynamics of power output. Shown are power of (a) upstream turbine and (b) downstream turbine. Simulated cases are operation of upstream turbine in nominal operation, and 1.8%, 4.4% and 7.0% derating.

The time series of the power output of the downstream turbines is shown in Figure 5-8b. It can be observed, that in case of a derating of the upstream turbine, the power output of the downstream turbine increases in some time periods. The fact, that the increase in power is only occasional and not continuous, is the effect of the overall turbulent flow in the wind farm. Particularly contributing effects are wake meandering, and the dynamics of turbine operation and wake propagation speed. As a result of wake meandering, the degree, to which the rotor of the downstream turbine is immersed in the wake of the upstream turbine, varies with time. Thus, the increased wind speed in the wake as a result of the derating at the upstream turbine is only at times beneficial for the downstream turbine. Further, the dynamics of turbine operation and wake propagation speed result in a varying time shift of the power output of the downstream turbine with respect to the case in which the upstream turbine is operating in nominal conditions. As a result, the change in power of the downstream turbine varies in time with respect to the nominal operation case. Because of these variations, the impact of induction-control on the power production of the two-turbine array is evaluated in a time-averaged manner in the following.

Figure 5-9 shows the effect of derating the upstream turbine on the time-averaged, total power output of the two-turbine array. It can be observed that derating the upstream
turbine reduces the time-averaged, sum power output of the two-turbine array. The percentage change in power output of the turbine array and the individual turbines is summarized in Table 5.3. In all cases, the increase in power of downstream turbine no. 2 is smaller than the reduction in power of the upstream turbine no. 1. Hence, the hypothesis that a positive offset of blade pitch angle at the upstream turbine could increase the total power of the two turbines is not supported by the results of the investigated LES cases.

![Diagram](image)

Figure 5-9: Effect of derating of upstream turbine on time-averaged total and individual power output of two-turbine array.

<table>
<thead>
<tr>
<th>Derating (%)</th>
<th>Turbine no. 1 Change in power in %</th>
<th>Turbine no. 2 Change in power in %</th>
<th>Two-turbine array Change in power in %</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>-1.8</td>
<td>0.7</td>
<td>-1.1</td>
</tr>
<tr>
<td>0.2</td>
<td>-4.4</td>
<td>2.3</td>
<td>-2.5</td>
</tr>
<tr>
<td>0.4</td>
<td>-7.0</td>
<td>3.5</td>
<td>-4.0</td>
</tr>
</tbody>
</table>

Table 5.3: Effect of downregulation of upstream turbine no. 1 on power output of downstream turbine no. 2 and sum power of two-turbine array. Two-turbine array comprises both turbine no. 1 and turbine no. 2.

Due to its higher fidelity, the results of the LES EllipSys3D tool are considered more trustworthy than the ones from sDWM and sPossPOW. The larger modelling uncertainty of sDWM and sPossPOW is likely to be the reason for the off-prediction in the results of the parametric study. It is unlikely that induction-control based on a positive offset of the pitch angle is beneficial in other external conditions. This is because the LES study was set-up in the potentially, most beneficial, external conditions observed in the parametric study of this work. It, however, remains open if a different stability regime of the ABL could yield a gain in total power. To conclude, the results of the LES study support the evidence from other investigations based on numerical [47] and experimental methods [42, 43]. These studies also show a reduction of total power when using a positive offset of the pitch angle at the upstream turbine.
Fatigue Load Impact

The LES show that induction-control based on a positive offset of pitch angle can yield a beneficial reduction of fatigue loads. Figure 5-10 shows the effect of derating on selected DELs of the wind turbines.

Figure 5-10: Effect of derating upstream turbine on damage-equivalent loads of wind turbines of two turbine array. Shown are (a) blade-root bending moment, (b) tilt moment, and (c) yaw moment. Damage-equivalent load is quantified using the rainflow counting algorithm.

The DELs are normalized with the DEL of the upstream turbine operating in nominal conditions. It can be observed that the largest impact of derating materializes in the DELs of the downstream turbine. The derating from 0% to 1.8% increases the loads at the downstream turbine on blade root and tilt by 4.5% and 1.8%, respectively. The change of yaw DEL is only 0.05%. The further derating of the upstream turbine to 4.4% and 7.0% results in a reduction of all investigated DEL at the downstream turbine. At a derating of 7.0% the reduction is 12% for the blade root DEL, 7.4% for the tilt DEL, and 7.4% for the yaw DEL. The effect of derating the upstream turbine on its own DELs is less pronounced. Blade root DEL and tilt DEL are reduced by up to 0.7% and 2.0%, respectively. Yaw DEL is increased by a maximum of 1.5%.

To conclude, the results of the LES study show that a positive offset of the pitch angle at the upstream turbine can be used to reduce the fatigue loads of a downstream turbine. It is of importance, however, to consider that the DELs of the downstream
turbine can first increase with derating. Derating the turbine further can then result in a successive decrease of DELs. Induction-control can therefore be used for the trade-off between power production and fatigue loads of wind turbines in nominal operation as investigated, for example, by Kanev et al. [114].

5.4 Summary

Induction-control based on a positive offset of the pitch angle can be used for the trade-off between power production and fatigue loads in nominal wind farm operation. The approach yields a beneficial reduction of the sum fatigue loads of a two-turbine array simulated in LES. As such, derating the upstream turbine by 7.0% effects at the downstream turbine a reduction of 12% in the blade root DEL, of 7.4% in the tilt DEL, and of 7.4% in the yaw DEL. The resulting change of DEL at the upstream turbine ranges between a reduction of 2.0% and an increase of 1.5%. The LES hereby quantify for the first time the trade-off between power production and fatigue loads during nominal wind farm operation using LES. Furthermore, the LES results can be used as reference for the verification of lower fidelity wind farm models used for optimizing nominal operation.

The use of a positive offset of the pitch angle at an upstream turbine has shown mixed outcomes with respect to its effect on the total power production of a wind farm. Yet, the investigations in literature only comprise selected external conditions. The present work therefore covers a wide range of external conditions. LES show that even in the potentially, most beneficial external conditions the approach results in a reduced total power production. It is therefore uncertain if the approach could be used to increase the total power production of a wind farm.
Chapter 6

Integration of Turbine Control Architecture

This chapter investigates the design of turbine control useful for enabling induction-based wind farm control discussed in chapter 5. The present standard turbine controller is unsuited for induction-control and therefore a new control approach is presented in this work. The developed controller uses a new downregulation strategy and thereby yields the desired reduction of thrust upon a decrease of turbine power. The employed downregulation strategy changes aerodynamic power by adjusting the blade pitch angle, even below rated rotor rotational speed. First, the controller is compared with the standard turbine controller in terms of static operation curves and dynamics of a single turbine. The comparison provides insight into the working principles of the controller that result in a reduced thrust. Next, the controller is tested in a wind farm set-up in dynamic simulation. The wind farm is operated in power control and induction-control mode by the DTU Wind Farm Controller. The SWF simulation results show the suitability of the developed turbine control approach for induction-control and power control of wind farms. This work thereby demonstrates an integrated solution for induction-control comprising both the control of the individual wind turbines and the entire wind farm.

Chapter 5 is based on publication [C1].

6.1 Introduction

When testing induction-control using a dynamic turbine model or a physical wind turbine, the offset in blade pitch angle is usually manually prescribed in the turbine controller. Thus, at present, the wind farm controller cannot effect an offset in pitch angle at wind turbines. In order to enable this, either the turbine control architecture could be modified or a set-point for the offset in blade pitch angle could be added to the controller inputs. The prior, that is changing the control approach, provides several advantages. First, the turbine remains a self-sustained unit with the robustness of operation ensured by the turbine control system. Second, the pitch angle might be simultaneously used for other turbine control procedures such as individual pitch control, and thus, setting the pitch angle externally could hamper the performance of these procedures. Third,
the inputs to the turbine system remain in line with the IEC norm [48]. Therefore, the modification of the turbine control architecture is being investigated in recent studies, typically with focus on the downregulation strategy.

The downregulation strategy defines the coordinated change of the blade pitch angle and rotor rotational speed used to adjust a turbine’s aerodynamic power. It thereby defines the effect of changing the power set-point on the pitch angle and rotor speed, which in turn impacts the thrust of the turbine. The thrust influences the wake flow. As a result, the downregulation strategy can be used to influence the effect of the power set-point on wake flow. Consequently, the wind farm controller can coordinate the impact of wind turbines on wake flow using the power set-point. In the downregulation strategy of a standard turbine controller, the aerodynamic power is regulated by controlling the rotational speed of the rotor. When reaching the rated rotational speed, the aerodynamic power is controlled using the blade pitch angle. Thus, reducing the power set-point, for example, below rated speed results in an increase in rotor speed. However, the desired effect for induction-control would be an increase in pitch angle and thus reduction in thrust. Therefore, in [38] several, new approaches for downregulating a wind turbine are introduced. An approach is to control the turbine aerodynamic power using the blade pitch angle, both below and above the rated rotor speed. The approach therefore allows to influence the pitch angle using the power set-point, as desired for induction-control. Consequently, the wind farm controller can adjust the power set-point of wind turbines in order to thereby implicitly control the pitch angle and thrust of these wind turbines. The approach is investigated in more detail in this chapter.

The contributions of this work are the following. First, the developed controller is compared with the standard turbine controller in static operation curves and the dynamics of a single turbine. The comparison provides insight into the working principles of the controller that result in a reduced thrust. Next, the controller is applied to a wind farm, which is operated in power control and induction-control mode by the DTU Wind Farm Controller. The dynamic simulations are conducted in SWF which simultaneously models turbine dynamics, wind farm flow aerodynamics and wind farm control. The simulation results show the suitability of the developed turbine control approach for induction-control and power control of wind farms. This work therefore demonstrates an integrated solution for the control of both the individual wind turbines and the entire wind farm.

The structure of the chapter is as follows. Next, the implementation of the downregulation strategy in a dynamic turbine controller is presented. Thereafter, the dynamic simulation framework used for the testing of this turbine controller is outlined including the employed framework for wind farm control. Finally, tests of the turbine controller on a single turbine set-up and a wind farm scale set-up are used to show the suitability of the proposed wind turbine control approach for induction-based wind farm control.
6.2 Methods

In the following, first turbine control concepts are being discussed and thereafter the test environment is presented for these controllers.

6.2.1 Wind Turbine Controller Design

The commonly used turbine controller is unsuited for induction-based wind farm operation strategies. Below rated rotational speed the employed downregulation strategy increases the turbine’s thrust. Above rated rotational speed, the optimum downregulation level is dependent on wind speed. Hence, a prediction of wind speed at the turbines in the wind farm would be required on the wind farm control level. It is not realistic to achieve such prediction at the accuracy required in order to realize a certain desired turbine operation. In the following, first the standard turbine controller is introduced, which is used as the reference controller design. Thereafter a novel turbine control approach is presented, which is suited for induction-based wind farm operation strategies and uses the ’Constant Tip-speed Ratio’ downregulation strategy introduced by Mirzaei et al. [38].

Constant Pitch Controller

The operation of the standard turbine controller, which is termed CPC in this work, is divided into two regions: below rated rotational speed and above. Below rated rotational speed, the power reference to the generator is set according to the maximum power point tracking (MPPT) approach, while the pitch angle reference remains constant. From rated rotational speed, the pitch controller becomes active and limits the generator rotational speed to the rated rotational speed. More information on the CPC can be found in [54].

Constant Tip-speed Ratio Controller

The main difference between the newly developed Constant Tip-speed Ratio Controller (CTSRC) and the standard CPC is the downregulation strategy used below rated rotational speed. The CTSRC aims to keep the tip-speed ratio of the wind turbine constant and controls aerodynamic power using the blade pitch angle. Figure 6-1 shows a schematic of the control system diagram of the CTSRC.

Below rated rotational speed, the pitch controller of the CTSRC sets the pitch angle reference $\beta$ as to deliver the aerodynamic power from the rotor that is required by the external power set-point $P_{set}$, but not exceeding the maximum available aerodynamic power $P_{avail}$. As such, the pitch angle is obtained from
Figure 6-1: Control system structure of 'Constant Tip-speed Ratio Controller’. Source: [C1]

\[
c_P(\lambda(u), \beta) = \frac{\min(P_{\text{set}}, P_{\text{avail}})}{\frac{1}{2}\rho\pi R^2 u^3}
\]  

(6.1)

where \(c_P\) is the turbine’s power coefficient and \(\lambda(u)\) the desired TSR given as a function of wind speed \(u\). \(\mu\) is the conversion efficiency from aerodynamic power to generator power, \(R\) the rotor length and \(\rho\) is the air density. The maximum available power \(P_{\text{avail}}\) is defined as

\[
P_{\text{avail}} = \frac{1}{2}\rho\pi R^2 u^3 c_P(\lambda(u), \beta = 0)
\]  

(6.2)

Below rated rotational speed, the power set-point to the generator is set with the objective to operate the turbine rotor at the desired TSR \(\lambda(u)\). This is achieved using a modified MPPT control strategy, which sets the generator power \(P_{\text{gen}}\) as a function of the generator rotational speed \(\omega_{\text{gen}}\), the blade pitch angle \(\beta\) and the wind speed \(u\) as

\[
P_{\text{gen}} = \frac{1}{2}\rho\pi R^5 c_P(\lambda(u), \beta) \frac{\omega_{\text{gen}}^3}{\lambda(u)^3 N_{\text{gear}}^3}
\]  

(6.3)

where \(N_{\text{gear}}\) is the gear ratio.

At rated rotational speed, the pitch controller is the same as in the CPC. The generator power \(P_{\text{gen}}\) is set to the minimum of turbine available power \(P_{\text{avail}}\), turbine rated power \(P_{\text{rat}}\) and turbine power set-point \(P_{\text{set}}\) as

\[
P_{\text{gen}} = \min(P_{\text{avail}}, P_{\text{rat}}, P_{\text{set}})
\]  

(6.4)
6.2.2 Simulation Framework

The dynamic investigations are carried out using the simulation framework SWF [55]. More information on the simulation model can be found in section 4.1.2 on the DFP. The wind turbines are controlled by one of the above presented turbine controllers that is either the CPC or CTSRC. The wind farm controller used in the simulations is the DTU Wind Farm Controller [8], as introduced in Section 2.

6.3 Results & Discussion

The impact of the developed CTSRC on the performance of the individual wind turbine and an entire wind farm is investigated in three case studies.

6.3.1 Case Study: Stationary Operation

The effect of the developed CTSRC on the stationary operation of a single wind turbine is investigated in this case study.

![Graphs showing power output, blade pitch angle, rotor speed, TSR, power coefficient, and thrust coefficient.]

Figure 6-2: Effect of developed CTSRC on the stationary operation of a single wind turbine with reference to standard CPC. Shown are (a) power output, (b) blade pitch angle, (c) rotor speed, (d) TSR, (e) power coefficient, and (f) thrust coefficient. Source: [C1]
Figure 6-2 shows a comparison of nominal and downregulated operation between the CTSRC and the CPC controller over the entire range of operational wind speeds. Below rated rotational speed, the CPC downregulates the turbine by increasing the rotor rotational speed while keeping the blade pitch angle constant as shown in Figure 6-2b and Figure 6-2c. The CTSRC, on the other hand, downregulates the turbine by increasing the blade pitch angle while keeping the TSR constant as depicted in Figure 6-2b and 6-2d. The resulting effect is a reduced thrust coefficient for operation with the CTSRC, while the turbine power and turbine power coefficient remain unchanged.

6.3.2 Case Study: Dynamic Operation

This case study demonstrates the effect of the CTSRC on the dynamic operation of the wind turbine. Reference to the operation of the CTSRC is the CPC. The case study is performed on an individual SWF turbine model equipped with either of the two turbine controllers. The simulation conditions are a constant wind direction and a step-wise varying wind speed, which is modelled as constant over the rotor area of the wind turbine. The power set-point of the turbine is 0.6MW.

Figure 6-3 shows the simulated operation of the turbine in terms of power, blade pitch angle, rotor rotational speed, TSR and thrust coefficient $c_T$. From time 0s to 200s and from 2200s to 2600s the available power of the turbine is less than the set-point. It can be observed that the use of the CTSRC results in a larger power output than the use of the CPC. The CTSRC controls the turbine to operate at the set of TSR and pitch angle.
that yields the maximum power coefficient. The CPC uses a different combination of TSR and pitch angle, and as a result the power output is lower. The different approach used in the CPC is not expected to be of general nature, but specific to the SWF turbine controller. From time 200s to 2200s the turbine is downregulated to the power set-point. As a result, the difference between the downregulation strategies of the two turbine control approaches is clearly visible. With larger downregulation the CPC increases rotational speed until rated speed and then increases the blade pitch angle. The CTSRC keeps the TSR constant and increases the blade pitch angle with larger downregulation. It can furthermore be observed that the use of the CTSRC results in a lower thrust than the use of the CPC. Consequently, wake-induced fatigue loads at a downstream turbine could be smaller with the use of the CTSRC as compared to the CPC.

6.3.3 Case Study: Integration with Wind Farm Control

This case study demonstrates the integration of the control of both the individual wind turbines and the entire wind farm. The results show the suitability of the CTSRC for use in induction-control and power control of wind farms. The case study is conducted on a three-turbine array that is spaced with 5D as shown in Figure 6-4. The simulated wind conditions are a mean wind speed of 8 m/s, a turbulence intensity of 8% and a mean wind flow direction aligned with the turbine row.

![Figure 6-4: Layout of simulated wind farm with turbine spacing of 5D. Source: [C1]](image)

The wind farm is operated in nominal operation from 0s to 1600s and from 3200s to 3600s and in power control mode between 1600s and 3200s. During power control, the wind turbines are coordinated using the closed-loop feedback controller, which employs the static dispatch function with an equal set-point distribution, as introduced in section 4.2.2. In nominal operation, the wind turbines are coordinated using the wind farm controller that aims to maximize the total power production. The controller uses the sPossPOW model to predict the operation of the wind farm. The optimized operation points of the wind turbines are, as such, derived from the optimization of the stationary wind farm operation. In order to account for the dynamics of wake propagation, the wind farm controller introduces the optimized operation points to the wind turbines in a time-shifted manner. Reference to the controller is the operation of the wind farm using the standard control approach, that is each turbine maximizes its individual power production. The purpose of operating the wind farm using the power maximizing controller is not to investigate if induction-control could increase total power production. The purpose is to demonstrate that the CTSRC allows a wind farm controller to coordinate the induction-control of wind turbines. It is, furthermore, to show that the consideration of the turbine control architecture in the development of wind farm controllers enables new, integrated control concepts.
Figure 6-5 shows the effect of the mode of operation and the approach of wind farm control on the dynamics of the blade pitch angle of the wind turbines. The difference between the sub-figures is the wind farm controller used during nominal operation. In Figure 6-5a the wind farm controller aims to maximize the total power of the wind farm. The controller introduces the optimized set-points to the turbines in a time-shifted manner to account for the delay in wake propagation. First, the set-point of turbine no. 1 is reduced and thereafter the set-point of turbine no. 2. The same actions can be observed after the switch from power control to nominal operation. Normally, with the CPC the reduced set-point would result in an increase of the rotor speed, while the pitch angle would stay constant. Using the CTSRC however, the pitch angle is increased and consequently, the thrust of these turbines is reduced as desired. This shows the possibilities of an integrated solution combining turbine control and wind farm control. For reference to the optimized nominal operation, in Figure 6-5b the wind farm controller lets each wind turbine maximize its individual power production during nominal operation.

Figure 6-5: Pitch angles of three turbine array with turbines controlled by CTSRC controller in power maximizing operation (0s – 1600s; 3200s – 3600s) and power reference following operation (1600s – 3200s). In power maximizing operation, the wind farm controller either (a) aims to maximize total farm power or (b) lets each turbine maximize its individual power output. Source: [C1]

Figure 6-6 shows the simulated total power of the wind farm and the reference signal during power control mode. The coordinated operation of the wind turbines in nominal operation results in an increase of 1% in the total power production. The increased pitch angle at upstream turbines reduces the wake deficit of the turbines and results in a power gain at downstream turbines and the entire wind farm. Albeit such increase is unlikely to be achieved in a real wind farm, as discussed in chapter 5, it shows the potential benefits of integrated solutions of wind farm control and turbine control. Such benefits could be gained in terms of fatigue loads. The positive offset of the pitch angle at upstream turbines is likely to reduce the fatigue loads at downstream turbines, as shown in chapter 5. Future work could make use of the effect by employing a model of turbine fatigue loads in PossPOW and thereby minimize fatigue loads in nominal operation. The use of the CTSRC would enable such operation on the turbine level.

Further during power control, it can be observed in Figure 6-6 that the total power of the
wind farm follows the reference accurately. The root-mean-square error is 0.3%, which is within the limits of the Danish grid code requirements [115]. It is therefore concluded that the CTSRC is well suited for both induction-control in nominal operation and for power control.

6.4 Summary

The CTSRC reduces turbine thrust in downregulated wind farm operation as compared to the standard approach, as demonstrated in stationary operation and the dynamics of a single turbine. The reduction in thrust is accomplished by downregulating a wind turbine using an increase in the blade pitch angle. Such operation can reduce fatigue loads at a downstream turbine, as shown in chapter 5. The wind farm case study shows that an integrated approach to the design of turbine control and wind farm control could improve the operation of wind farms. The simulation results furthermore show the suitability of the CTSRC for induction-control and power control of wind farms.
Chapter 7

Conclusions

A framework of an operational wind farm controller was developed in this thesis comprising solutions for power control and induction-control. Its major advantages are faster prototyping, design flexibility and a common environment for the development of wind farm control. These are facilitated by the modular program architecture of the framework in all relevant areas of its structure. The framework consists of five high-level units, that is a measurement processing unit, two wind farm controller units, a unit of data and models on the wind turbine cluster, and a unit on wind farm operation models. The unit on data and models of the wind turbine cluster comprises turbine-specific data storage and models of the wind turbines in the wind farm. The measurement processing unit performs pre-processing of raw measurement data and provides post-processed data to the wind farm control units upon demand. To improve flow model performance in wind farm controllers, the framework comprises tools for the accurate measurement of wind direction, wind speed and turbulence intensity.

Concerning turbulence intensity, the first analytical solution for the quantification of the spatial variance of second-order moment of wind speed was developed in this work. The approach is successfully verified using simulation and field data. The impact of the spatial variance on three, selected applications of the wind energy sector is then investigated including mitigation measures. First, the variance of the second-order moment between front-row wind turbines of Lillgrund wind farm is investigated. The variance ranges between 25% and 48% for turbulence intensities ranging from 7% to 10%. It is thus suggested to use the second-order moment measured at each individual turbine as input to flow models of wind farm controllers in order to mitigate random error. Second, the impact of the spatial variance of the measured second-order moment on the verification of wind turbine performance is investigated. Misalignment between the mean wind direction and the line connecting the meteorological mast and wind turbine results in a random error in the observed second-order moment of wind speed. Such random error brings uncertainty in turbulence intensity-based classification of the fatigue loads and power output of the wind turbine. To mitigate the random error it is suggested to either filter the measured data for low angles of misalignment, or to quan-
ify wind turbine performance using the ensemble averaged measurements of the same wind conditions. Third, the verification of sensors in wind farms can involve distant reference measurements. The suggested mitigation measures are the same as for the verification of turbine performance.

Three, innovative developments on power control are presented in this thesis, the Dynamic Flow Predictor, a model-optimized dispatch, and a fatigue-optimizing model-predictive controller. Model-based control approaches benefit from computationally fast, linear models and therefore, in this work the Dynamic Flow Predictor is introduced. It is a fast, control-oriented, dynamic, linear model of wind farm flow and operation that provides predictions of wind speed and turbine power. The model estimates wind turbine aerodynamic interaction using a linearized engineering wake model in combination with a delay process. The Dynamic Flow Predictor is tested on a two-turbine array to illustrate its main characteristics and on a large-scale wind farm, comparable to a modern offshore wind farms, to illustrate its scalability and accuracy in a more realistic scale. The simulations are performed in SimWindFarm with wind turbines represented using the NREL 5MW model. The results show the suitability and computational speed of the modelling approach. In the study on the large-scale wind farm, rotor effective wind speed is estimated with a root-mean-square error ranging between 0.8% and 4.1%. In the same study, the computation time per iteration of the model is on average $2 \times 10^{-5}$ s. It is therefore concluded that the presented modelling approach is well suited for the use in wind farm control.

At present, wind farms control their power production using a closed-loop feedback control approach, which distributes the total power to the wind turbines. However, the total power is distributed according to the turbines’ available power, only. The use of model-predictive control allows to consider multiple objectives, nonetheless, since it is open-loop, it can result in a poor tracking of the total power reference. This work is the first to combine the benefits of fast, closed-loop feedback control and model-predictive control for power control of wind farms. As such, an optimization-based dispatch function was developed for a closed-loop feedback wind farm controller. The dispatch function uses model-predictive, multi-objective optimization to determine the distribution of the total power demanded by the feedback controller. The model employed in the developed dispatch function is the Dynamic Flow Predictor, which uses a Kalman filter-driven feedback to correct the wind farm flow model dynamically. The developed, optimization-based dispatch function is compared to dispatch functions commonly employed in present wind farms in a secondary regulation scenario in dynamic simulation. The comparison is carried out on an eighty-turbine, large-scale wind farm. The newly developed, optimization-based dispatch function yields a reduction of the mean error and the normalized root-mean-square error by 43% and 36% with respect to the best-performing, commonly-used dispatch function. Furthermore, for the large-scale wind farm, the duration of the optimization is only 0.21s, that is two orders of magnitude faster than for comparable approaches presented in literature.

Cumulative operation and maintenance costs of offshore wind farms can amount to 38% of lifetime costs. In wind farms, upstream turbine wakes can result in up to 80% higher fatigue loads at downstream wind turbines. The present work therefore investigates to reduce wind turbine fatigue loads during the provision of grid balancing services using
model predictive wind farm control. The main objective of the developed controller is to follow a total wind farm power reference and to reduce the damage equivalent tower bending moments of the turbines in the wind farm. The control approach uses the Dynamic Flow Predictor to model the dynamics of wind farm flow. The developed two-turbine fatigue load model is used to estimate the impact of wind farm operation on fatigue loads. The model predictive controller is compared with commonly used wind farm control approaches in two wind farm case studies using a dynamic wind farm simulation tool. The simulation results suggest that the proposed model predictive controller can reduce the sum of the equivalent tower bending moments of wind turbines in a wind farm during provision of ancillary services. Simulations of an eight-turbine array show up to 28% lower sum equivalent tower moments as compared to commonly-used wind farm controllers. The observed reduction in turbine fatigue loads is attributed to the use of adequate wind farm-scale wind turbine fatigue load models.

Next, the use of induction-control in nominal operation of wind farms is investigated to mitigate power loss and fatigue loads. Large-eddy simulations provide, to the author’s knowledge, the first, high fidelity evidence on the impact of the approach on fatigue loads. It is observed that a positive offset of pitch angle yields a beneficial reduction of the sum fatigue loads of a two-turbine array. Derating the upstream turbine by 7.0% results in a reduction of damage-equivalent loads on the downstream turbine of 12% in the blade root, of 7.4% in the tilt, and of 7.4% in the yaw. The approach therefore allows for the trade-off between power production and fatigue loads in nominal wind farm operation. Using the approach to increase total power production has yielded mixed outcomes in literature. It is however unclear if the investigations were conducted in the most beneficial conditions. Therefore, in this work, a wide range of external conditions is analyzed. The [DWM] and Larsen wake model show the largest, potential power gain in low turbulence intensity and turbine spacing, and a wind direction aligned with the wind turbines. Even in these potentially most beneficial conditions, large-eddy simulations show reduced total power production when using an offset of the pitch angle at the upstream turbine of a two-turbine array. It is therefore uncertain if the approach could increase total power.

Thereafter, the design of turbine control is investigated as to enable induction-based wind farm control. The present standard turbine controller is unsuited for induction-control and therefore a new control approach is presented in this work. The developed controller uses a new downregulation strategy and thereby yields a reduction of thrust upon a decrease of turbine power. The employed downregulation strategy changes aerodynamic power by adjusting the blade pitch angle, even below rated rotor rotational speed. First, the controller is compared with the standard turbine controller in terms of static operation curves and dynamics of a single turbine. The comparison provides insight into the working principles of the controller that result in a reduced thrust. Next, the controller is tested in a wind farm set-up in dynamic simulation. The wind farm is operated in power control and induction-control mode by the DTU Wind Farm Controller. The simulation results show the suitability of the developed turbine control approach for induction-control and power control of wind farms. This work thereby demonstrates an integrated solution for induction-control comprising both the control of the individual wind turbines and the entire wind farm.
To conclude, in this thesis a framework for the control of wind farms was developed comprising solutions for power control and induction-control. To improve flow model performance in wind farm controllers, the framework comprises tools for the accurate measurement of wind direction, wind speed and turbulence intensity. The developed model-predictive, closed-loop feedback controller allows for the operation of wind farms in power control according to multi-objectives. The approach is based on the newly developed Dynamic Flow Predictor and a novel fatigue load model. The approach thereby provides a possible solution to the open challenge to accurately track the reference for the total power of the wind farm, while reducing the fatigue loads of wind turbines in the wind farm. The investigations on induction-control demonstrate that even in the potentially, most beneficial conditions an increase in total power is not observed in large-eddy simulations. It thus remains uncertain if such control can be used to increase total power. However, it is shown that the approach is suited to trade-off between total power and fatigue loads and can be realized in present wind turbines using a newly developed wind turbine controller.
In future work, the developments of this thesis could be advanced to higher levels of technology readiness. As such, the DFP could be extended to include further dynamics relevant to wind farm operation. Most importantly, dynamic changes of wind direction, and the prediction of the wind speed at upstream turbines. Modelling changes of wind direction can be introduced using a heuristic method that starts and ceases wind speed delay procedures to wind turbines upon changes in wind direction. The prediction of the wind speed at upstream turbines can be achieved by the use of an auto-regressive model. The advantage of such approach is its suitability for integration into the state space model of the DFP.

Next, it is of interest to extend the two-turbine fatigue model to allow for the modelling of large-scale wind farms. Thereafter, the extended model could be augmented with an optimization algorithm. As a result, operation strategies that reduce fatigue loads can be obtained for use in power control.

After having undertaken the above two developments, the power controller with model-predictive dispatch function could be tested in high fidelity simulations to demonstrate its performance. Such tests could path the way for the experimental testing of the control approach.

With regards to nominal operation, the sPossPOW and sDWM models could be extended with a model on the effect of yaw misalignment on wake flow. Thereby these models could be used to derive operation strategies for yaw steering.
Bibliography


