ACTIVE ROBUST CONTROL OF WIND TURBINES

by

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The research work conducted in this thesis focuses on robustness of wind energy conversion system with respect to faults in pitch actuator in order to prevent unnecessary emergency shutdown, and keep the turbine operational without significant inefficiency in its overall performance. The objective is to investigate the feasibility of using a fault estimator and a light detection and ranging (LIDAR) system as additional sensors to design a suitable control system for wind turbines. Robust control technique is used to address these issues.

Three controllers are proposed in this work that try to address sources of inaccuracy in wind turbine operation:

An active fault tolerant controller is first designed using a fault estimator. It is shown that a set of locally robust controllers with respect to the fault, together with a suitable smooth mixing approach, manages to overcome the problem of faults in the pitch actuator.

To address the wind-dependent behavior of turbines, a second controller is designed using the LIDAR sensor. In this configuration, LIDAR provides the look ahead wind information and generates a smooth scheduling signal to provide active robustness with respect to the changes in wind speed.

Lastly, utilizing both the fault estimator and LIDAR, a 2-dimentional wind-dependent active fault tolerant controller is developed to control the wind turbine in region 3 of operation.

The feasibility of the proposed ideas is verified in simulation. For this purpose, the US National Renewable Energy Laboratory’s FAST code is used to model the 3-balded controls advanced research turbine. A discussion on practical considerations and ideas for future work are also presented.
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<th>Description</th>
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<tr>
<td>BLC</td>
<td>Baseline controller</td>
</tr>
<tr>
<td>CART2</td>
<td>2-bladed controls advanced research turbine</td>
</tr>
<tr>
<td>CART3</td>
<td>3-bladed controls advanced research turbine</td>
</tr>
<tr>
<td>DEL</td>
<td>Damage equivalent load</td>
</tr>
<tr>
<td>DOF</td>
<td>Degree of Freedom</td>
</tr>
<tr>
<td>DTC</td>
<td>Disturbance tracking control</td>
</tr>
<tr>
<td>FAST</td>
<td>Nonlinear aero-elastic turbine simulation code</td>
</tr>
<tr>
<td>FDI</td>
<td>Fault detection and isolation</td>
</tr>
<tr>
<td>FTC</td>
<td>Fault tolerant control</td>
</tr>
<tr>
<td>HAWT</td>
<td>Horizontal axis wind turbine</td>
</tr>
<tr>
<td>LIDAR</td>
<td>Light detection and ranging</td>
</tr>
<tr>
<td>LPV</td>
<td>Linear parameter varying</td>
</tr>
<tr>
<td>LTI</td>
<td>Linear time invariant</td>
</tr>
<tr>
<td>MMC</td>
<td>Multiple-model control</td>
</tr>
<tr>
<td>MPPT</td>
<td>Maximum power point tracking</td>
</tr>
<tr>
<td>NREL</td>
<td>National renewable energy laboratory</td>
</tr>
<tr>
<td>NWTC</td>
<td>National wind technology center</td>
</tr>
<tr>
<td>PID</td>
<td>Proportional integral derivative</td>
</tr>
<tr>
<td>QFT</td>
<td>Quantitative feedback theory</td>
</tr>
<tr>
<td>RMS</td>
<td>Root mean square</td>
</tr>
<tr>
<td>VAWT</td>
<td>Vertical axis wind turbine</td>
</tr>
<tr>
<td>VSWT</td>
<td>Variable speed wind turbine</td>
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<tr>
<td>WECS</td>
<td>Wind energy conversion system</td>
</tr>
<tr>
<td>WT</td>
<td>Wind turbine</td>
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To my family
CHAPTER 1
INTRODUCTION

The general trend in wind technology is discussed in this chapter starting with an overview of global wind energy capacity. Different types of wind turbines (WTs) and their operation regions are then introduced with the goal of presenting the main control objectives and potential control inputs for each region. In addition, the challenges in control of WTs are highlighted through a survey of the state-of-the-art in WT control. The chapter will conclude with a description of the structure of the thesis.

1.1. Statistical Overview

As a clean alternative to fossil fuels, renewable energy has attracted considerable interest among the power grid operators and policymakers within the past 10 years, to the extent that the installed capacity of renewable power exceeded 1470 GW at the end of 2012[1]. As a fast growing renewable energy resource, wind energy continues to contribute to the power grids around the world, with a total capacity of 296,255 MW by the end of June 2013, i.e., amounting to 3.5% of the global electricity demand [1]. Figure 1.1 depicts the total installed capacity of wind energy during the period from 2010 to 2013 [1].

![Total installed wind energy capacity (in MW) for the period 2010-2013. Reproduced from [1].](image)

Figure 1.2 shows the top markets of wind technology in the world in 2013 [1]. The market for wind energy in the United States was assisted by the increasing trend in manufacturing
turbine components, in addition to improvements in WT design which could lead to increased turbine efficiencies. Around 45% of all new electricity generation in the US is based on wind energy [2]. To be able to respond to larger demands, the size of the turbine would have to be increased; for example a typical 5 MW WT has a tower of approximately 114 m high, with a rotor diameter of 124 m [3]. However, increasing the size of WTs would result in an increase in its overall cost. This in turn calls for advanced control strategies that enable the turbine to achieve more electrical energy from the available wind, while at the same time reducing the maintenance cost.

1.2. Wind Turbine Overview

A WT works based on the principles of lift and drag forces as a result of wind blowing towards the turbine blades. These forces turn the turbine, and therefore the rotor of the generator which is coupled to the turbine, thereby producing electrical energy. Based on the configuration and layout of the blades and their rotation plane, WTs are classified as vertical axis wind turbine (VAWT) or horizontal axis wind turbine (HAWT). HAWT is more complex and more expensive than VAWT; however, it is more popular due to its higher efficiency. In terms of the way the generator rotor is connected to the turbine’s rotor, a WT can be classified as direct-drive, where the turbine’s rotor is directly coupled to the electrical generator, or gearbox-based, where the gearbox divides the power shaft into a low speed shaft on turbine side and a high speed shaft on the generator side. In this thesis, a gearbox-based HAWT is used in the analysis mainly due to its popularity in wind industry. Figure 1.3 shows the 2 and 3-bladed controls advanced research
turbines (CART2 and CART3) of the US national renewable energy laboratory (NREL) located at national wind technology center’s (NWTC) wind farm near Boulder, CO.

The main components of a HAWT are:

1. Hub and Blades: The blades convert the wind energy to rotational displacement, and hub connects the blades to the low speed shaft.
2. Low-Speed Shaft: This shaft connects the rotor to the gearbox.
3. Gearbox: Connects the low-speed shaft to the high-speed shaft. It increases the rotational speed of low-speed shaft to make it match the required rotational speed of the generator.
4. High-Speed Shaft: This connects the gearbox to the electrical generator to allow for the conversion of mechanical energy into electrical energy.
5. Electrical Generator: Produces electrical energy.
6. Brakes: Are used to stop the WT either at normal or emergency situations.
7. Nacelle: This is where the low and high speed shafts, the brakes, the generator, and other relevant components are located.
8. Tower: Since there is more wind power at higher elevations, the tower lifts the rotor and nacelle up to an optimum level above the ground.

Fig. 1.3: CART2 and CART3. Picture courtesy of NREL.
In addition to the classifications mentioned earlier, a HAWT can be a fixed-speed WT or a variable-speed WT (VSWT). In the case of the latter, the WT can be further subdivided based on the type of control scheme, namely, stall control, active stall control or pitch control [4]. The fixed-speed WTs are simple in design, are cheap, can be directly connected to the grid, and can be designed in such a way that the maximum aerodynamic efficiency of the turbine is achieved at a fixed speed. However, pitch-controlled VSWTs are selected in this study due to the fact that their power electronics interface makes it possible to study the WT independent of the power grid dynamics and the related frequency issues, and provides a better control authority on a wide range of wind speeds.

To better determine the control objectives, the operational regions of the WT are often divided into different regions as described below (see Fig. 1.4) [5]:

1. Region 1: At this region, wind speed is below the cut-in value and the wind power is not enough to turn the rotor. Here, the pitch angle is set to produce the minimum aerodynamic torque, and the turbine is off-work.

2. Region 2: An increase in wind speed increases the wind power, and the rotor starts to turn. Now, the pitch angle is kept at its optimum value in order to produce the maximum aerodynamic torque. At this region, the control input is limited to the generator torque command in order to achieve maximum power point tracking (MPPT) via control of the generator speed.

3. Region 2 - 1/2: This is a fictitious region where the wind speed is getting close to its rated value and is often modeled to assist with a smooth transition between regions 2 and 3. Here, the generator torque command is calculated such that the rated power of the generator will be achieved at rated wind speed. As a result, mechanical stress will be decreased with a safe switching approach. Normally, both pitch angle and generator speed are considered the control inputs at this region.

4. Region 3: Here, the wind speed is above the rated value, and the control mechanism starts to limit the power absorption. The torque input is constant and the pitch command input is utilized in order to control the rotor speed and consequently maintain the aerodynamic power at its rated value. Power regulation, mechanical load reduction and safe operation are the main objectives at this region.
5. Region 4: At this region, wind speed exceeds the cut-out value and the turbine falls into its normal shut-down process. Usually, loads on WTs which result from the high wind speed, and the safety concerns at shut-down time are the main operation challenges at this region.

![Diagram of Regions of Operations in WTs.](image)

Fig. 1.4: Regions of operations in WTs. The wind power is proportional to the cube of wind speed (black curve); however, theoretically, a WT can absorb up to only 59% of the wind power (green curve). The red curve shows the power curve of a typical wind turbine with $C_p < 0.5$.

From a mathematical point of view, the rotor of a turbine absorbs wind power through equation (1-1)[6].

\[
P_r(\lambda, \theta) = \frac{1}{2} \rho \pi R^2 V^3 C_p(\lambda, \theta)
\]

\[
\lambda = \frac{R \omega_r}{V}
\]

where $P_r$ is the rotor power, $\lambda$ is tip speed ratio which is defined as the ratio of rotor tip speed to the wind speed, $\rho$ is the air density, $R$ is the length of the blades, $V$ is the wind speed, $C_p$ is the power coefficient of the turbine, and $\omega_r$ is the rotor speed. Figure 1.5 shows the coefficient $C_p$ for CART which is obtained by WT-Perfcode [7].

1.3. Wind Turbine Control

A survey of literature on advanced control strategies for WTs indicates the following as the main design challenges:

1. Wind disturbances affect the performance of the closed loop system.
2. Unmodeled dynamics impact the stability and performance of the closed-loop system.
3. The main source of the nonlinearity in WTs, i.e. the \( C_p \) function, is unknown, and changes during the course of operation of a WT.

4. WT dynamics indicate wind-dependent behavior, which means that the parameters of a WT model are different at different wind speed operating points.

5. Wind speed estimation or light detection and ranging (LIDAR) measurements of wind speed may have inaccuracies.

6. Faults may occur in the components of the wind energy conversion system (WECS).

In the rest of this chapter, the strategies adopted in the literature to address some of these challenges are briefly pointed out.

![Graph](image)

Fig. 1.5: CART’s \( C_p \) surface as a function of pitch angle and tip speed ratio.

1.3.1. Nonlinear Feedback Control

As illustrated in Fig. 1.5, the \( C_p \) surface is a nonlinear function of the pitch angle and the tip-speed ratio (or rotor speed and wind speed). Consequently, aerodynamic torques and bending moments are nonlinear functions of wind speed, pitch angle and rotor speed [5]. This would naturally indicate that precise reference tracking in WECS can be better achieved through nonlinear control methodologies.
This issue has been addressed in the literature. For example, a feedback linearization control strategy was introduced in [8] to handle the problem of nonlinearity in WTs and to separate the wind disturbance from the dynamics of the turbine. The authors used the same model for both controller design and simulation, and reported promising results.

WTs are complex systems with many subsystems and coupled modes as depicted in Fig. 1.6 where not all of these modes are considered in the design process of the controller. However, these unmodeled dynamics may adversely affect the stability and performance of the overall closed-loop system. For example, a similar feedback linearization method as in [8] was adopted in [9] to control the CART coded with FAST; however, it led to different results. These mismatches between the results can be due to adoption of a simplified WT model for controller design purposes, which can further underline the effect of unmodeled dynamics as one of the controller design challenges.

Fig. 1.6: Interconnection of subsystems in a WT and the effects of the environment. Modified from [10], with permission.
Another source of inaccuracy in the design of feedback linearization based controllers comes from the assumption of having an analytical function for $C_p$. Although it is common in the literature to assume a known $C_p$ surface and accordingly design nonlinear or lookup-table-based strategies for control of WTs [11], this function is in general unknown and furthermore, it changes over time for an installed WT [12]. This means that control systems designed based on the assumption of known $C_p$ may not be reliable for the purpose of long-term operation; although, more efficient controllers may be able to address this issue to some extent. For example, in [13], sliding mode nonlinear control strategy was adopted as an alternative for feedback linearization technique. This controller is inherently robust with respect to either nonlinearity in the behavior of the system or the effect of disturbances. However, chattering in the controlled output may impose some restrictions on pitch actuators and therefore question the feasibility of such controllers for control of WTs at region 3. By increasing the complexity of the original design, the authors of [13] introduced a higher order sliding mode controller combined with a sliding mode observer in order to solve the chattering problem for generator torque control of WTs [14]. In another case, a novel nonlinear control method has been developed in [15] to control both speed and power of the generator in a cascaded configuration. Also, in order to increase the captured energy and decrease the mechanical load, Kalman filtering was used in [16] in combination with a nonlinear dynamics state feedback controller.

Regardless of the results, as also noted in [17]–[18], using a nonlinear controller may lead to instability or limit cycle issues as well as the lack of realizable analytical solutions. Hence, while WT has a nonlinear behavior and it is verified through simulations that nonlinear control methods improve the performance of WECSs, in practice, linear controllers tend to be more popular within the wind industry.

1.3.2. PID and Optimal Feedback Control

It is easy to show that a proportional integral derivative (PID) controller is robust with respect to constant disturbances. Therefore, under the assumption of having piecewise constant wind disturbances, PID has been widely used to control WTs. PID-based control of WT is discussed in detail in [19]. However, since the linearized WT model depends on the wind speed parameter, even in the absence of any unmodeled dynamics, the parameters of a WT model would vary from one wind speed operating point to another. This means that a PID would not be able to provide any guarantees for general stability of the linear WECS. In order to solve this
problem, gain-scheduled PID has been used to control the WT [20]-[22]. The basic idea is to design different PIDs at different wind speed linearization points and find a scheduling function based on interpolation of the controllers in order to adjust the loop gain appropriately. In this technique, pitch angle and wind speed can be considered as the scheduling parameters. Although this controller shows improved performance in comparison to the conventional approach; similar to the PID method, the design would be sensitive to the unmodeled dynamics.

Other control techniques have also been proposed in the literature. For example, authors in [23] apply a novel multivariable controller to control CART with the objective of achieving reasonable power regulation while ignoring modeling uncertainties. In other instances, researchers have used multivariable control theory in order to satisfy multiple objectives simultaneously. Authors in [24] simulated a $H_{\infty}$ optimal control for WT's without considering modeling uncertainties. Authors of [21] and [25]-[30] used the theories of disturbance tracking control (DTC), disturbance accommodating control and disturbance utilization control in state-space in order to solve the multi-objective control problem of WT's. Since they estimated the wind speed, these methods were efficient in reducing the effect of wind disturbances; however, wind-dependent behavior of WT's was not considered in their analysis.

The concept of DTC was enhanced in [31] in order to address the periodic behavior of WT dynamics. However, this would still be ineffective with regards to the unmodeled dynamics of the WT. In order to achieve to a better closed-loop performance, a higher-order model of WT is required that inevitably increases the complexity of the design procedure. Moreover, in this case, the need for observability would force the designer to utilize additional sensors which would in turn add to the cost of the controller.

1.3.3. Robust Feedback Control

As pointed out in [6] for CART, unmodeled dynamics may lead to poor performance and instability of the WECS. To address this and in order to be able to control plants with modeling uncertainties, passive robust control methods have been adopted [32]-[33]. Geng and Yang [34] introduced a nominal inverse-model based controller augmented by a robust compensator to mitigate the effects of nonlinearities and the disturbances. Using this approach, they achieved a robust tracking of the power command. Quantitative feedback theory (QFT) is another robust control methodology in frequency domain which uses feedback values in order to either reduce
the effect of modeling uncertainties or satisfy the desired performance of the closed-loop system. This idea was applied to control of WT in [35]. Nevertheless, these solutions do not consider the wind-dependent dynamics of the turbine. To make matters worse, conventional robust controllers lead to very conservative designs for WTs, especially if all aforementioned design challenges are taken into account.

Linear parameter varying (LPV) control is another scheme which has been used in the literature to maximize the energy captured, address the unmodeled dynamics of WTs, and consider its wind-dependent behavior [36]-[40]. This method addresses all aforementioned challenges in linear control of WTs while assuming a measured or estimated wind speed as an independent parameter. In another instance, the author of [35] developed a switching-QFT robust controller to enhance the QFT controller proposed in [18]. Also, authors in [41] designed a multiple-model controller (MMC) for distinct wind speed linearization points to consider the wind-dependent behavior of WTs. However, this approach is not robust with respect to the unmodeled dynamics, and the overall performance is sensitive to the accuracy of wind speed estimation. Additionally, this does not provide any guarantees for transients from one wind speed operating point to another.

1.3.4. Adaptive Feedback Control

Adaptive control could partially solve the problem of wind-dependent behavior of WTs. This method has been evaluated in [42]-[48] and [51]-[53]. Authors of [42] applied a self-tuning regulator as a step towards adaptive control of WT. A generalized model predictive control was used in [43] as another adaptive approach for pitch control of WTs. A multi-input multi-output self-tuning regulator was simulated in [44] to regulate the output power, and also to decrease the load on WT. Authors of [45]-[47] argued that the uncertainty in the aerodynamic parameters of a WT may lead to non-optimality in tracking of maximum power points of WT. To address this, they used adaptive control ideas to find optimal solutions that could overcome the lack of knowledge about aerodynamic properties of WTs. All these methods showed improvements; however, in general, they do not provide guarantees for stability and performance with respect to unmodeled dynamics. In [48], direct adaptive control strategy of [49] was modified to regulate the generator speed of CART at its rated value while considering wind speed disturbance. In addition to the modeling uncertainty, the main difficulty of this method lies in its assumption on
having a strictly positive real system which may restrict its applicability [50]. However, this problem is solvable for single-input single-output model of WT. In [51], the method of [48] was improved to separate the non-strictly positive modes from other modes in order to overcome the previous problem and consider the structural modes of WTs. Also, adaptive DTC was developed in [52] to relax the assumption of having a WT with known parameter values, and was applied for torque control of CART. In [53], an adaptive partial state feedback DTC augmented with wind speed estimator was developed and applied to NREL’s 5MW WT. Due to the complexity in the design of adaptive controllers for turbulent wind profiles, the simulations were limited to a step-like wind speed profile. Nevertheless, these methods are still not considered robust with respect to modeling uncertainties.

To simultaneously address the unmodeled dynamics uncertainty, wind-dependent behavior of WTs, and wind disturbance input in the linear control of WTs, the authors of [54] modified the conventional feedback robust model reference adaptive control idea of [50] and developed a robust adaptive feedback-feedforward pitch controller for CART. Here, the feedforward term was based on adaptive estimation of the changes in wind speed, and the method was verified for both step-like and turbulent wind profiles.

### 1.3.5. Feedforward Control

As an alternative approach for estimation of wind speed, Fig. 1.7 shows how the LIDAR sensor provides information about the wind speed at a distance in front of the turbine [55]-[57]. In many references, researchers have used LIDAR information for control of WTs, where a trade-off is made between the reference tracking (or regulation) and mechanical load minimization in order to achieve to their control objectives[58]-[60]. The ideas are very similar to each other and follow the feedforward control theories. These strategies are referred to here as direct LIDAR-based control of WTs, as represented by Fig. 1.8. This configuration allows for redesigning the original feedback part with the goal of reducing the required actuation signals [61]. In another work, [62] used a LIDAR-based model predictive control loop in addition to the preview feedback controller in order to improve some of the performance indices in control of WTs. However, LIDAR measurement inaccuracies together with the effect of unmodeled dynamics and disturbances in the measurement path can magnify the effect of modeling uncertainties in the feedback loop and may lead to instability of the WECS.
The authors of [63] used optimal filtering approach to reduce the effect of measurement errors on direct LIDAR-based control schemes. They showed that LIDAR measurement errors in the conventional feedforward strategy could degrade the performance of the closed-loop system. However, they did not consider the unmodeled dynamics or the wind-dependent behavior of the WT model.
1.3.6. Fault Tolerant Control

Regardless of the efficiency of the control ideas discussed earlier, WECSs need different sets of sensors and actuators in order to implement the control schemes. These components are subject to different abnormalities and faults. It is therefore important to investigate the effects of actuator and sensor malfunctions on the general behavior of the closed-loop system (e.g., on power tracking error), and design a controller that enables the WECS to operate successfully in the presence of these unwanted situations. Fault tolerant control (FTC) is a well-researched topic in the control systems literature and is suitable to compensate for these abnormalities [64]-[66]. FTC is typically divided into two groups: passive and active, as is illustrated in Fig. 1.9 [66]. Passive control uses different robust control methodologies to address the problem of faults with only a single controller. On the other hand, active control usually includes a fault detection and isolation (FDI) unit in addition to estimating one or more fault parameters and actively tuning the control signal based on fault conditions. Here, FDI is used to identify the plant condition and send the required commands to the plant accordingly.

To further describe Fig. 1.9, three different cases have been assumed: normal (no fault), fault #1, and fault #2, which are distinguished from one another by using different colors. Each circle shows the possible set of controllers for the corresponding case, and the stars represent the best controller for each scenario. Active FTC would then make it possible to switch among the stars while passive FTC would be restricted to the intersections of solutions for all cases. Hence, while the closed-loop performance by a passive FTC is limited (even for the no fault case), the system works with its best possible performance for different cases under an active FTC. Simplicity in design and implementation of the passive controllers is its main advantage, whereas active FTC is characterized through superior performance. However, the main drawback of passive FTC is the fact that, similar to any other robust control technique, the general solution is only available when the local solutions intersect. Figure 1.10 demonstrates this drawback of passive FTC where it has been shown that active FTC is able to handle the non-intersecting case.

Despite the fact that FTC is widely used in different applications, it is relatively unexplored within the WT field of study. Much of the work in this field focuses on FDI techniques [67]-[71] and is based on the first WT fault tolerant benchmark model presented in [72]. Few instances have been reported on WT FTC [39],[40] and [54]. However, as discussed in [73], it is desired
for WTs to keep working under faulty conditions, which further justifies the need to investigate the FTC techniques for WTs. This is the main topic of the research work presented here.

Fig. 1.9: Passive vs. active FTC. Both passive and active control ideas can be used to design a controller.

Fig. 1.10: Passive vs. active control, non-intersecting case. Only active control technique has a solution for this problem.
1.4. Contribution of the Current Work

From an application point of view, based on the author’s best knowledge, the proposed design is the first active robust controller to address the problems of fault in the actuator, wind-dependent dynamics behavior, and wind speed disturbance. In particular:

1. The main objective of this research is to design fault tolerant pitch controller for control of WTs at region 3 of operation. Since the information about different faulty cases is available, LPV modeling is used to describe pitch actuator based on a fault parameter. Then, a set of local robust controllers are designed that are passively robust against local changes in the fault parameter. To globalize guarantees for robustness against faults, a fault estimator is used to measure the fault parameter. Then, this measured parameter is used to actively determine the correct local controller within the loop. It should be mentioned that the final controller is passively robust against unmodeled dynamics. Additionally, reducing the effect of wind speed disturbances on the measured generator speed is the other control objective that is guaranteed through utilizing robust control technique. Furthermore, assuming a fixed design structure, an innovative idea is proposed to systematically determine the number of local passive controllers through an iterative approach.

2. Proposed active design idea is used to address the problem of wind-dependent dynamics in WTs. In this case, a wind speed dependent LPV model is formulated to design different local controllers. Then, LIDAR wind speed measurement is used as the scheduling signal to adaptively change properties of closed-loop WECS depending on wind speed operating point.

3. The previous two designs are combined to adaptively adjust properties of the closed-loop WECS based on fault and wind speed parameters. Here, similar to the second design, it is important to capture parameter-dependent properties of WT’s dynamics. Thus, the systematic local linear model design procedure of FTC controller is no longer applicable.

Remark: It should be noted that the systematic procedure proposed in FTC design could be used for wind-dependent designs in order to determine the number of local controllers based on the required disturbance rejection property of the closed-loop system. However, it is preferred to predetermine the number of local controllers and instead, capture the wind-dependent behavior of the WT’s dynamics through the change of the weighting functions.
1.5. Structure of the Thesis

The rest of this thesis is organized as follows: Problem statement is presented in Chapter 2. Chapter 3 provides a literature survey on available strategies suitable to meet the control objectives of this research. The basics of the theory behind the proposed control idea are also introduced in this chapter. Chapter 4 formulates the WT problem and sets the design requirements. To investigate the feasibility of the proposed method, the simulation results are presented in Chapters 5 and 6. Finally, Chapter 7 discusses the practical consideration issues, implementation requirements, as well as concluding remarks and suggested future work to continue this research.
CHAPTER 2
PROBLEM STATEMENT

Based on the discussion of Section 1.3, the following list is now introduced as the main technical challenges in controlling WTs:

1. Unknown time-varying nonlinearity in WTs,
2. The effect of wind disturbance on the performance of the closed-loop system,
3. The effects of unmodeled dynamics on the stability and performance of the closed-loop system,
4. Wind-dependent WT dynamics,
5. Faults in the components of the WECS,
6. Inaccuracy of the LIDAR measurements.

The objective of this research is not to simultaneously address all the above design issues; however, as discussed below, it is intended to fully or partially resolve some of these concerns.

The first design challenge points out that the nonlinear model-based control strategies that use the \( C_p \) function are not necessarily reliable. Robust nonlinear control strategies could be investigated instead in order to find a solution for this problem. These designs are not considered here; although, they have been addressed in the literature for general nonlinear systems.

With or without LIDAR, the second design issue has generally been addressed in the WT literature through adopting feedforward strategies. As an alternative to direct LIDAR-based control strategies, the solution put forth in this research can be seen as another technique for wind speed disturbance rejection. In the proposed solution, this control objective is achieved by defining the desired control performance without wind speed measurement.

The third design issue is completely well-known in the control theory literature, and is usually addressed through utilization of robust control techniques. Robust control is the foundation of the proposed solution in this research.

The fourth and fifth design issues highlight the uncertainties in the parameters of WT linear models. An appropriate control technique needs to be designed based on a suitable parameter-dependent model for the WT. LPV and gain-scheduling techniques have traditionally been used for problems of this nature, and may be suitable for the purpose of WT control as well. However, robust adaptive control strategies are in general considered to be superior in the presence of
uncertainties, yet, there is only one reference that partially considers the above issues by using robust adaptive schemes in the time domain [54]. With the goal of achieving a better performance, the scheme proposed here is developed in the frequency domain, as further discussed in Chapter 3.

Due to its importance, the fifth design challenge has also attracted a lot of attention in the literature, and is well-researched. The proposed methodology here, although not the only solution, is able to address these fault conditions as well.

The sixth challenge is investigated in [63] for direct LIDAR-based techniques. This aspect is also addressed in the proposed control strategy without introducing any additional complexities in the controller design.

2.1. A Brief Overview of the Proposed Control Strategy

Active robust control technique adopted in this research is a special case of robust adaptive control schemes, and potentially is able to address design challenges 2 through 6 discussed in the previous section. For this reason, this technique has been proposed and analyzed here as a possible solution for the WT control application. In this approach, advantages of frequency domain robust design can be further enhanced with the time-domain properties of the active control concept. In the frequency-domain, different, and sometimes contradictory, design objectives can be satisfied through an appropriate design tradeoff, while in the time-domain, the conservativeness of the design can be reduced by considering parametric uncertainties separately. More specifically, in the frequency-domain, the mixed $\mu$-robust control formulation is used as a tool that provides guarantees for both robust stability and robust performance by the use of maximum possible knowledge of the WT model. This basically results in an in-depth model-based control design, and has a less conservative design compared to conventional robust control approaches.

The big picture for this design is as follows:

1. A suitable WT model for robust control design purposes is developed here as illustrated in Fig. 2.1, where the required notation for this figure is discussed in detail in Chapter 4.
2. Robust mixed $\mu$-synthesis method is determined to be suitable to solve the design problems of this thesis. In order to apply this technique, the model in Fig. 2.1 is augmented with some weighting functions (see Chapters 5 and 6) and transformed into the generalized plant $P(s)$ as illustrated in Fig. 2.2. Then, the robust stability and robust
performance are locally guaranteed by \( \mu \) robust control theory. Further information about this method is described in detail in Chapter 3.

3. To globalize the robustness guarantees, a mixing (bumpless switching) scheme is applied in order to generate the global control signal based on a set of local control signals. The general idea of this approach is introduced and discussed in Chapter 3.

4. This technique has been applied here for designing FTCs for WT application in Chapters 5 and 6. In all cases, generator speed is considered to be the measured signal, and the blades’ collective pitch angle is the control input to the WT. In addition, fault and wind parameters are measured by the fault estimator and the LIDAR sensor, respectively.

Fig. 2.1: Uncertain wind-dependent model of the augmented actuator-WT with fault in the actuator. The complex-valued unmodeled dynamics uncertainty \( \Delta \), real-valued wind-dependent uncertainty \( \delta_{ud} \) and real-valued fault uncertainty \( \delta_{f} \) are separately addressed in this approach.

![Diagram](image.png)

Fig. 2.2: General scheme for the mixed \( \mu \) design

### 2.2. Outline of the Research Work

The research work conducted here first considers two different problems independently of one another: (a) fault in the actuator and (b) wind-dependent behavior of WT model. This helps simplify the problem and verify the feasibility of the proposed idea. To address (a), the FTC design uses a fault estimator within the loop, whereas in the wind-dependent design to address
LIDAR is incorporated. For the second design, inaccuracy in LIDAR measurement is partially addressed through the available degree of freedom of the design.

In the next step, a mixed model is proposed that is now able to consider both aspects simultaneously. For this wind-dependent active FTC, both fault estimator and LIDAR are used to provide exact knowledge on the fault condition and wind speed, respectively.

In all cases studied, the uncertainties associated with the unmodeled dynamics are also taken into account. Moreover, in all cases, wind speed disturbance rejection is addressed with the help of robust control formulation in the frequency-domain.
CHAPTER 3
ACTIVE ROBUST CONTROL

Increasing the size, flexibility, and cost of WT's further underlines the need for advanced controllers that are able to obtain more energy from the wind power while keeping maintenance costs as low as possible. As discussed in Chapter 1, various advanced methodologies have been developed to control the WT with different control objectives in mind. In this chapter, the problem of non-idealities in modeling is briefly discussed. Then, a case is made for the concept of active robust control as a suitable solution to this problem.

3.1. Modeling Uncertainty

Modeling of a given system is the first step in the design of model-based controllers. The physical system can be very complex and may include some unknown dynamics; therefore, finding a low-order mathematical representation of the system that completely describes its behavior over all possible operating conditions is a difficult task. In control theory, this simple mathematical model must show a reasonable approximation of the physical system at low frequencies (determined based on the control objectives). However, due to the effect of unmodeled dynamics, the model may not provide a good approximation of the system performance at high frequencies. In order to overcome this problem, the theory of robust control introduces ways to represent the modeling uncertainties, either as structured or unstructured blocks.

Assume \( G_0(s) \) corresponds to the modeled low frequency dynamics of the system. Then, modeling uncertainty can be divided into dynamics uncertainty and parametric uncertainty.

3.1.1. Dynamics Uncertainty

This uncertainty exists as a result of ignoring some of the plant dynamics in order to obtain a low-order linear time-invariant (LTI) model. In multiplicative uncertainty, the nominal model \( G_0(s) \) and the physical system \( G(s) \) are related to one other through equation (3-1):

\[
G(s) = G_0(s)(1 + \Delta_m(s)).
\]  
(3-1)

where \( \Delta_m(s) \) is the multiplicative uncertainty term. This function is unknown, but it satisfies inequality (3-2) in frequency domain for a scalar uncertainty:

\[
|\Delta_m(j\omega)| \leq \delta_m(\omega) \quad \forall \omega,
\]  
(3-2)
where $\delta_m$ is known. This gives a family of uncertain systems as in (3-3):

$$\Pi_m = \{ G \mid \left| \frac{G(j\omega) - G_0(j\omega)}{G_0(j\omega)} \right| \leq \delta_m(\omega) \}. \quad (3-3)$$

In robust control, $G_0$ is assumed completely known and the uncertainty in modeling is represented by $\Delta_m$. In robust adaptive control, it is further assumed that the parameters of $G_0$ are unknown as well. Thus, it is not necessary to consider the effects of deviation in poles and zeros in $\Delta_m$. Consequently, in this thesis, the only assumption regarding $\Delta_m$ is that it has to be stable. Figure 3.1 shows the block diagram of the multiplicative uncertainty.

![Fig. 3.1: Multiplicative uncertainty representation.](image)

### 3.1.2. Parametric Uncertainty

In this scenario, the nominal LTI model $G_0(s)$ is assumed to have a fixed structure for a known range of changes in its parameters. This uncertainty in parameters of $G_0(s)$ could be due to:

a. Limited knowledge on the parameters: In this case, the parameter is constant but only an approximation of its value is known.

b. Changes in the operating point: In this case, the parameter varies as a result of the changes in the operation condition. The knowledge about the parameter can be exact, but only for a special operating point.

Independent of the source of uncertainty, the parametric uncertainty can be modeled with a multiplicative formulation. For example, if parameter $\alpha$ is uncertain with a range of change indicated as $[\alpha_{\text{min}}, \alpha_{\text{max}}]$, then the uncertain parameter is determined to be $\alpha = \bar{\alpha}(1 + r_\alpha \delta_\alpha)$ where the nominal parameter is $\bar{\alpha} = \frac{\alpha_{\text{min}} + \alpha_{\text{max}}}{2}$. Additionally, $r_\alpha = \frac{\alpha_{\text{max}} - \alpha_{\text{min}}}{\alpha_{\text{max}} + \alpha_{\text{min}}}$ denotes the weight of uncertainty, and $|\delta_\alpha| \leq 1$ is an unknown bounded scalar.

### 3.2. Active Robust Control; General Idea

In the most general case, a controlled system comprises different parts, namely a plant (maybe nonlinear and time varying) and a set of sensors and actuators. The system could be
subjected to different abnormalities and non-idealities in its components. Additionally, some controllers are model-based which means a model of the plant is incorporated into the controller design procedure. In this case, uncertainty in the modeling of the plant as well as malfunctions of actuators and sensors can affect the behavior of the closed-loop system (e.g. the tracking error). This justifies the need for designing a controller that enables the closed-loop system to operate successfully in the presence of any deviations from the normal condition. Borrowing the concepts of FTC from Chapter 1, it is possible to design either passive or active controllers to address these problems. Despite having a simpler solution, a passive controller has some disadvantages:

1. It has no solution when there is no intersection among the solutions for different sub-problems (see Figs. 1.9 and 1.10),
2. It shows a limited performance when it tries to provide guarantees for several design issues.

Active control is therefore a more appropriate choice for controlling systems with several sources of uncertainties. These methods can be divided as follows:

1. Adaptive control techniques with robust adaptation rules,
2. Multiple-model robust control strategies with an adaptive switching mechanism.

The first approach is based on the robustness of the adaptation algorithm and is usually implemented in the time domain. For example, [75] proposed least-square method with parameter projection modification for adaptation rule, [76] introduced a backstepping approach together with dead-zone modification for adaptation, and [77] used a minimum variance approach with dead-zone modification. However, in normal cases, the achieved robustness in adaptation leads to a poor performance of the overall closed-loop system compared to the conventional adaptive controllers (e.g., an increased tracking error) [50]. To address this, [78] developed a multi-layer dead-zone modification of the adaptation algorithm in order to reduce the steady state error of the closed-loop system. In [79], the dead-zone modification rule was improved in order to completely remove the steady state error associated with a step reference command. This idea was further developed by adding an adaptive disturbance change estimator for WT control problem while there were no restrictions on the reference command signal [54]. A summary of other notable studies on robust adaptation rules are summarized in [50] and will not be repeated here.
The main benefit of the previous method lies in its simplicity in implementation. However, when there is sufficient information about the plant, using a frequency domain approach leads to an in-depth design comparing to the one in time domain. For this thesis, this is achieved by utilizing an active robust control strategy. Here, robustness is accomplished through designing locally robust controllers, while adaptiveness is provided through soft transition among these different controllers. This is done in such a way that, at any point in time, the most appropriate controller operates in the loop. This idea is known by different names based on the differences in the analysis tools. For example, references [80]-[81] discussed this topic as robust adaptive technique. Authors of [82]-[83] referred to it as a switching system and author of [84]-[85] introduced this concept as supervisory control. Regardless of the name, this approach should provide a smooth transition between various controllers in order to ensure the stability of the overall closed-loop system [86].

In the current research, ideas put forth in references [74],[81],[87]-[89] are used to provide a stable active robust controller with guaranteed performance for WTs. The basic idea is to:

1. Address the effect of unmodeled dynamics via designing locally robust controllers,
2. Parameterize the faults in the pitch actuator with a measurable parameter in order to design active FTC for WTs,
3. Measure the wind speed in order to design an active robust controller to address the problem of wind-dependent behavior of WTs,
4. Mix the local controllers with an appropriate stable logic,
5. Combine the ideas of #2 and #3 in order to have a wind-dependent active robust FTC for WTs.

The idea proposed in this research is illustrated in Fig. 3.2 where the behavior of the plant over the entire region of operation is demonstrated by a behavior-parameter (one or two dimensional). It is then divided into a few sub-regions, where a different locally robust controller is developed for each one. Finally, the global controller functions by switching through the local controllers using a measured behavior-parameter. One advantage of this approach is that designing local controllers with robust techniques helps reduce the total number of required controllers. In addition, such a scheme provides a theoretical guarantee for robust stability and robust performance over the entire region of operation.
The main advantage of the active robust control idea lies in the fact that it does not need precise knowledge about nonlinear model of the physical plant. In other words, this is a closed-loop performance based design. This concept is similar to velocity-based linearization gain scheduling technique where the local models are designed based on the required modeling accuracy, assuming no unmodeled dynamics and exact knowledge on the nonlinearity of the plant. The main goal of the velocity-based linearization gain scheduling in [90]-[92] is to solve the potential problems of conventional gain scheduling technique (e.g., see [93]). For example, the velocity-based linearization gain scheduling does not need to operate at equilibrium points. Moreover, it considers the transition between the equilibrium points which are used to design local controllers in conventional MMC approaches. However, for WT control applications, the main problem is the lack of the knowledge about the nonlinearity of the turbine that makes the velocity-based linearization impossible, which means that only linear models obtained at different equilibrium points are available to synthesis the controller. On the other hand, because of having parametric robustness provided by the active robust controller, transition between equilibrium points is not critical for the proposed strategy in this thesis. Hence, considering the robustness with respect to the unmodeled dynamics, the strategy proposed here is a better solution than velocity-based linearization method.

Fig. 3.2: General scheme of active robust control.
3.3. Passive Robust Controller; An Overview

There are different techniques for designing robust controllers, namely $H_\infty$, $H_2$ and mixed $H_2/H_\infty$. In short, $H_\infty$ is a suitable strategy for reference tracking problems, $H_2$ is well-suited for feedforward control design, and mixed $H_2/H_\infty$ would simultaneously achieve both objectives.

In this research, command tracking is an important objective; however, $H_\infty$ technique only considers the robust stability problem, and assumes complex-valued uncertainties in the system. Hence, if adopted, $H_\infty$ technique would result in a conservative design for a system with real-valued parametric uncertainties (e.g., WT control problem of this research). On the other hand, $\mu$-robust controller provides a framework for both robust stability and robust performance. Additionally, it is able to distinguish the real-valued parametric uncertainty in modeling from the complex-valued uncertainty due to the unmodeled dynamics, which means the final design would be less conservative compared to the $H$ methods. Figure 3.3 shows the difference between assuming a real-valued uncertainty and a complex-valued uncertainty in a model parameter. Here, the real part of the uncertain parameter changes between [0,1]. Therefore, by assuming a real-valued uncertainty, the set of uncertain plants would be limited to the red line. However, without any knowledge about the type of the uncertain parameter, a complex-valued model is assumed which would naturally expand the set of uncertain models to a circle with center of 0.5 and radius of 0.5. Consequently, the controller will be more conservative because of the increased number of possible plants.

Fig. 3.3: Real [red] vs. complex-valued [blue] uncertain models.
3.3.1. Design Issues

In traditional time domain robust adaptive controllers, the number of control objectives are typically limited (see [50]). However, a correctly-designed passive robust controller can address many design issues. In the current research, the basic design criteria to be met by the controller are:

1. Stability,
2. Reducing the effects of unmodeled dynamics (robust stability),
3. Reducing the effects of fault and wind parametric uncertainties (robust stability),
4. Reference tracking with uncertainty in modeling (robust performance),
5. Disturbance rejection with uncertainty in modeling (robust performance),
6. Reducing the actuator usage with uncertainty in modeling (robust performance).

In the literature of robust control theory, these issues are typically addressed under the topics of robust stability and robust performance. In the next section, \( \mu \)-robust controller will be briefly discussed as a solution providing combined robust stability and robust performance. However, the details of this topic fall outside the scope of the current work, and more in-depth analysis is provided in [94], [74] and [89].

3.3.2. \( \mu \) Robust Control Design

The basic idea of \( \mu \) robust control design is to have an iterative algorithm in order to minimize the structured singular value \( \mu \) over a specific frequency range (\( \mu \) will be defined later). In the DK-iteration method (see [74]), \( H_{\infty} \) design algorithm is combined with the \( \mu \) analysis tool in order to find the \( \mu \) controller at each iteration. To do this, the configuration of Fig. 3.4 should be obtained for the given system where \( P(s) \) represents the generalized plant that includes the model of the system, actuators, and some weighting functions to optimize or penalize the corresponding performance outputs. \( P(s) \) can be partitioned as in (3-4).

\[
P(s) = \begin{bmatrix}
P_{11} & P_{12} & P_{13} \\
P_{21} & P_{22} & P_{23} \\
P_{31} & P_{32} & P_{33}
\end{bmatrix},
\]

(3-4)

The top block is the structured uncertainty matrix that is defined as:

\[
\Delta l = \{\text{diagonal}[\delta_1 l_1, ..., \delta_l l_l, \Delta_{l+1}, ..., \Delta_n]\}.
\]

In this study, \( \delta_l \) is considered to be a real-valued scalar uncertainty and \( \Delta_j \), a complex-valued uncertainty, is also assumed to be a scalar since the system under study is single-input single-
output. $K$ is the controller to be designed. Also, $y$ is the measured output, $u$ is the control signal, $w$ represents the external inputs, and $z$ is the vector of performance outputs. Similar to [89], the input-output of uncertainty block $\Delta l$ is omitted for simplicity in notation of this section.

Fig. 3.4: General configuration for robust control design.

If the controller is viewed as a component of the system, the overall framework would change to Fig. 3.5 where $N$ is the lower linear fractional transformation and has a 2 by 2 partitioned format as in (3-5). This structure is useful for robust stability analysis by small-gain theorem.

$$N(P, K) = \begin{bmatrix} N_{11} & N_{12} \\ N_{21} & N_{22} \end{bmatrix} = F_1(P, K) = \begin{bmatrix} P_{11} & P_{12} \\ P_{21} & P_{22} \end{bmatrix} + \begin{bmatrix} P_{13} \\ P_{23} \end{bmatrix} K(I - P_{33}K)^{-1} \begin{bmatrix} P_{31} \\ P_{32} \end{bmatrix}, \quad (3-5)$$

Fig. 3.5: General configuration for robust stability analysis.

Theorem 3.1. Small gain theorem (adopted and simplified from [89]):

Assuming an unstructured uncertainty block $\Delta l$ with $\|\Delta l\|_\infty \leq 1/\gamma$, the robust stability of the $N - \Delta l$ structure of Fig. 3.5 is guaranteed if $\|N\|_\infty \leq \gamma$. Then, if $\gamma = 1$, it is sufficient to have $\|N\|_\infty \leq 1$.

For robust performance analysis, an equivalent robust stability problem with an additional uncertainty block $\Delta P$ with $\|\Delta P\|_\infty \leq 1$ should be verified, as shown in Fig. 3.6. This is equal to the $N - \Delta l$ structure of Fig. 3.5 with no external inputs and outputs.
For synthesis, the controller $K$ should be considered separately. The configuration will be as shown in Fig. 3.7 where the outer uncertainty loop $\Delta P$ (in blue) is added to model and address issues related to robust performance, the $\Delta l$ component is used to represent both parametric and dynamics modeling uncertainties, and $K$ is the controller that needs to be designed appropriately.

The uncertainties are now combined to form $\Delta_{DK}$ block that represents both robust stability and robust performance:

$$\Delta_{DK} = diag\{\Delta l, \Delta P\},$$

The design criteria for this scheme are as follows (see [74] and [89]):

1. **Nominal Stability:** $NS \iff N$ should be internally stable. In other words, $K$ stabilizes the closed-loop system with the nominal plant model. This is related to item 1 in Section 3.3.1.
2. **Nominal Performance**: \( NP \iff \|N_{22}\|_\infty < 1 \) for \( \Delta_p \) (i.e., there is no modeling uncertainty). Thus, NP indicates that items 4, 5 and 6 of Section 3.3.1 are satisfied for the nominal model without parametric and dynamics uncertainties.

3. **Robust Stability**: \( RS \iff \|N_{11}\|_\mu < 1 \) for \( \Delta I \) uncertainty block. In this case, the stability of the closed-loop system is achieved for all uncertain plant models. Therefore, RS is related to the items 2 and 3 in Section 3.1.1.

4. **Robust Stability and Robust Performance**: \( RSRP \iff \|N\|_\mu < 1 \) for \( \Delta_{DK} \). This is obtained based on Theorem 3.1 for the system in Fig. 3.7 (i.e., with structured uncertainty \( \Delta_{DK} \)). By incorporating the structure of \( \Delta_{DK} \) into the equation above, the condition can be expressed as \( \mu_{DK}(N) \geq \max\{\mu_{\Delta I}(N_{11}), \mu_{\Delta p}(N_{22})\} \). Hence, this indicates that the stability and performance of the closed-loop system are guaranteed for the uncertain system with \( \Delta I \). In other words, using the \( \mu \) synthesis idea leads to a controller that guarantees all items in Section 3.1.1. It should be mentioned that the performance requirements are defined through the \( z \) vector in Fig 3.8, and are further explained in Chapter 5.

Here, peak- \( \mu \) value is determined to be as shown in (3-6).

\[
\|N\|_\mu = \sup_{\omega} \mu_\Delta(N(j\omega)), \tag{3-6}
\]

where the structured singular value \( \mu_\Delta \) is defined as in (3-7):

\[
\mu_\Delta(N) \triangleq \frac{1}{\min_{\Delta \in \Delta}(\bar{\sigma}(\Delta) \text{ s.t. } I - N \Delta = 0)}, \tag{3-7}
\]

The details of this formulation are explained in [89], Section 11.2. In the next step, the robust stability and robust performance problem would be defined as solving the inequality (3-8) for \( K \):

\[
\inf_{K} \sup_{\omega} \mu_\Delta(N(P,K)) < 1, \tag{3-8}
\]

Since the stability is insensitive to scaling (see [74], Section 8.7), a new scaled system \( M \) would have the same stability as the original \( N \) in Fig. 3.8:

\[
M \triangleq D^{-1}ND,
\]

where \( D \) is the block-diagonal scaling matrix corresponding to the \( \Delta_{DK} \) block. Consequently, the RSRP problem is redefined as the inequality (3-9):

\[
\inf_{K} \sup_{\omega} \mu_\Delta(DM(P,K)D^{-1}) < 1, \tag{3-9}
\]

However, no general mathematical solution exists for this equation. Therefore, the DK-algorithm uses \( \bar{\sigma}_\Delta \) as an upper bound estimation for \( \mu_\Delta \) and solves inequality (3-10) iteratively in order to find the required controller \( K \).
In the next chapters, the generalized plant $P(s)$ of Fig. 3.7 will be developed for the WT application. Then, Matlab (see [95] and [96]) will be used to implement the DK-iteration algorithm to find controller $K$.

As an outcome of this design, $\mu$-value would indicate the level of robustness for both stability and performance of the closed-loop system such that (a) when $\mu = 1$, the system is on the boundary of stability and performance robustness, and cannot tolerate any more uncertainties, (b) when $\mu < 1$, the system can tolerate more uncertainty for RSRP problem. For example, if $\mu = 0.8$, then it is possible to increase the level of modeling uncertainty (length of parametric uncertainty in this thesis) or increase the performance demand (through the performance outputs) by 25%, (c) when $\mu > 1$, the system is not robust, and either the modeling uncertainty level or performance requirements should be decreased. Further information on this aspect is provided in [89].

3.4. Global Control Signal via Mixing

Having a set of stable closed-loop systems does not necessarily mean that the global controller obtained by the switching between those stable systems will be stable. The following example shows the importance of an appropriate selection of switching logic for multiple model control strategies.

Example:

Assume there are two different stable systems making up a time varying system as:

$$x(k + 1) = A(k)x(k),$$

$$A(k) = \begin{cases} A_0, & k \text{ is even} \vspace{0.5em} \\ A_1, & k \text{ is odd} \end{cases},$$

$$A_0 = \begin{bmatrix} 1.0299 & -0.9048 \\ 1 & 0 \end{bmatrix} \text{ and } A_1 = \begin{bmatrix} 1.0299 & 1 \\ -0.9048 & 0 \end{bmatrix}. $$

Both $A_0$ and $A_1$ have eigenvalues less than 1 and are stable with $|\text{eig}(A_0)| = |\text{eig}(A_1)| = [0.9512, 0.9512]$. They also have similar SVD decompositions as $A_0 = USV'$ and $A_1 = VSU'$ where $S = \begin{bmatrix} 1.5999 & 0 \\ 0 & 0.5656 \end{bmatrix}$. So, if $x_0 = v_1$ where $v_1$ is the 1st column of $V$, then:

$$x(1) = A(0)x(0) = A_0x_0 = USV' * v_1 = 1.5999u_1,$$
where \( u_1 \) is the 1\(^{st}\) column of \( U \). Then, for next sample, we need to switch to the other system:

\[
x(2) = A(1)x(1) = A_1x(1) = VSU' \ast (1.5999u_1) = (1.5999)^2 v_1.
\]

Thus,

\[
x(k) = \begin{cases} 
1.5999^k \ast v_1, k \text{ is even} \\
1.5999^k \ast u_1, k \text{ is odd}
\end{cases}
\]

It was illustrated through this example that a bad switching logic between two stable systems could lead to an unstable system.

In the current research, the mixing strategy of [87]-[88] is used to provide a continuous combination of local controllers with smooth transition. In order to mix the control commands, the scheduling signal \( s \) is measured. This is the same as the uncertain parameter for the proposed active robust control idea. Then, a trapezoidal function (3-11) is created where \( a, b, c \) and \( d \) are design parameters.

\[
F(s, a, b, c, d) = \begin{cases} 
0 & s < a \text{ or } s > d \\
\frac{s-a}{b-a} & a \leq s \leq b \\
1 & b \leq s \leq c \\
\frac{d-s}{d-c} & c \leq s \leq d
\end{cases}
\] (3-11)

Consequently, the global control command would be obtained through the combination of all \( N \) local controllers as in (3-12):

\[
u = \sum_{i=1}^{N} \frac{F_i(v_f,a_i,b_i,c_i,d_i)}{\sum_{j=1}^{N} F_j(v_f,a_j,b_j,c_j,d_j)} u_i
\] (3-12)

The proof of stability is discussed in [87] and will not be detailed here.

### 3.5 Active Control Design Procedure

In this thesis, two parametric uncertainties have been considered, a fault parameter and a wind parameter. This would create a two-dimensional uncertainty plane. Ideally, for such a problem, a large (perhaps infinite) number of non-robust local controllers would be necessary to ensure acceptable performance in the presence of parametric uncertainties over the entire uncertainty plane (see Fig. 3.7). This is clearly impractical. An active robust strategy such as the one proposed here reduces this number by introducing locally robust controllers, each one replacing several non-robust controllers (see Fig. 3.8). This way, the problem becomes feasible and implementable. This concept is the focal point of the proposed work, and detailed design steps are described in Chapters 5 and 6.
Fig. 3.8: The big picture to show how active robust control design in (b) can provide theoretical guarantees on a wide range of changes in parameters with fewer number of local controllers comparing to the non-robust control design in (a). In (a), different controllers are designed at intersections of vertical and horizontal blue lines while in (b), each controller guarantees robustness for one square. In both non-robust (a) and robust (b) control ideas, the activeness is achieved through the switching between the local controllers.
CHAPTER 4
MODELING OF WIND TURBINES FOR ROBUST CONTROL SYNTHESIS

This chapter starts with an introduction to modeling of WTs using NREL’s nonlinear aeroelastic turbine simulation code (FAST). Then, it provides the general formulation to model the WT suitable for the objectives of this thesis. The models developed in this chapter will be used for the design of the robust controller in the next chapters.

4.1. Modeling by FAST Code

Various studies have been reported in the literature that assume exact knowledge on the nonlinearity of WT, and model the WT based on the knowledge of different subsystems in Fig. 1.6 connected together (e.g., see [8] and [97]). In the current research, FAST code [98] is used to model the CART3. This code provides different degrees of freedom (DOF) as outlined in Table 4.1[6].

Table 4.1: DOF provided by FAST code to model the mechanical and electrical subsystems of a 3-bladed on-shore wind turbine. Aerodynamic Torque calculation has its own DOF (not shown in this Table).

<table>
<thead>
<tr>
<th>DOF</th>
<th>Physical interpretation</th>
</tr>
</thead>
<tbody>
<tr>
<td>$q_1$</td>
<td>First flapwise blade mode</td>
</tr>
<tr>
<td>$q_2$</td>
<td>Second flapwise blade mode</td>
</tr>
<tr>
<td>$q_3$</td>
<td>First edgewise blade mode</td>
</tr>
<tr>
<td>$q_4$</td>
<td>Drivetrain rotational-flexibility</td>
</tr>
<tr>
<td>$q_5$</td>
<td>Generator</td>
</tr>
<tr>
<td>$q_6$</td>
<td>Yaw</td>
</tr>
<tr>
<td>$q_7$</td>
<td>First fore-aft tower bending-mode</td>
</tr>
<tr>
<td>$q_8$</td>
<td>Second fore-aft tower bending-mode</td>
</tr>
<tr>
<td>$q_9$</td>
<td>First side-to-side tower bending-mode</td>
</tr>
<tr>
<td>$q_{10}$</td>
<td>Second side-to-side tower bending-mode</td>
</tr>
</tbody>
</table>

This provides (4-1) as a comprehensive nonlinear model of WT useful for simulation purposes [98]:

$$M(q, \beta, t)\ddot{q} + f(q, \dot{q}, \beta, u_d, t) = 0$$

(4-1)
where $M$ represents the mass-matrix, $f$ stands for force function, $q$ denotes the displacement of DOF vector, $\dot{q}$ is the rate of the DOF, $\ddot{q}$ shows the acceleration of the DOF, and $t$ is time. In this research, $\beta$ is the collective pitch angle control input and $u_d$ is the hub-height wind speed disturbance.

Having access to the required data files to model different components of a WT (e.g., tower data set), FAST numerically solves (4-1) during the simulation timeframe. On the other hand, in order to obtain the linear model of the WT, it assumes a constant wind speed and outputs (4-2) as a function of rotor azimuth position $\psi$, where $d$-variables represent the displacements around the linearization point of any of the DOF variables:

$$M(\psi).d\dot{q} + C(\psi).d\dot{q} + K(\psi).dq = F(\psi).d\beta + F_d(\psi)du_d$$

(4-2)

After some manipulation, a periodic linear model of the WT can be obtained as a set of linear time invariant models at different azimuth positions:

$$\begin{align*}
\dot{x} &= A(\psi)x + B(\psi)\beta + B_d(\psi)u_d \\
y &= C(\psi)x + D(\psi)\beta + D_d(\psi)u_d
\end{align*}$$

where $x = [dq^T, \dot{dq}^T]^T$. Finally, an azimuth-averaged model can be used as the overall LTI model of WT at a specific wind speed linearization point:

$$\begin{align*}
\dot{x} &= Ax + B\beta + B_du_d \\
y &= Cx + D\beta + D_du_d
\end{align*}$$

(4-3)

If all DOF listed in Table 4.1 are enabled, the linear model (4-3) will include 32 states. Yaw control is beyond the study of pitch and torque controls of WTs, and is therefore ignored here. Even then, not all remaining states are required for control design purposes. Therefore, only a fifth order linear WT model is used in the rest of this research. In this model, two states represent symmetric flapwise displacement of the rotor, two states are used to model drivetrain torsion, and the final state denotes the generator speed variable. The rest of the states are assumed to represent the unmodeled dynamics which are used for verification of the robust control design.

Here, $y$ is the measured generator speed. Also, $A \in \mathbb{R}^{5 \times 5}$, $B \in \mathbb{R}^{5 \times 1}$, $B_d \in \mathbb{R}^{5 \times 1}$ and $C \in \mathbb{R}^{1 \times 5}$ are the system matrices, and $D$ and $D_d$ are zeros. It should be noted that the model in (4-3) does not include the pitch actuator dynamics. The actuator is assumed to be given by (4-4).

$$\beta = \frac{\omega_n^2}{s^2 + 2\xi_0\omega_n s + \omega_n^2}u,$$

(4-4)
where $\xi_0$ is the damping ratio and $\omega_{n,0}$ is the natural frequency for ideal actuator. Also, $u$ is the control command provided by controller. When the actuator dynamics are incorporated into the WT model (4-3), the overall pitch actuator-WT augmented model will be given as in (4-5), which is depicted in Fig. 4.1.

$$\begin{align*}
\dot{x} &= Ax + Bu + B_d u_d \\
y &= Cx + Du + D_d u_d
\end{align*}$$

(4-5)

![Diagram of Augmented pitch actuator-WT model](image1)

Fig. 4.1: Augmented pitch actuator-WT model.

### 4.2 Unmodeled Dynamics

As mentioned earlier, despite the possibility of having a 30th order linear model for the WT, only a 5-state model is assumed to be known for the purpose of this research. Thus, a first order multiplicative weight in the form of (4-6) is used to compensate for the effect of unmodeled dynamics (modified from [74]).

$$w_{wt} = k_{wt} \frac{b_1 s + b_0}{a_1 s + a_0} u,$$

(4-6)

where $k_{wt}$, $a_1$, $a_0$, $b_0$, and $b_1$ are design parameters. This way, the nominal model of Fig. 4.1 changes to the uncertain model of Fig. 4.2 which includes the complex dynamics uncertainty block $\Delta$. This form of modeling is useful for designing passive robust controllers with respect to the unmodeled dynamics uncertainty.

![Diagram of Uncertain augmented pitch actuator-WT model](image2)

Fig. 4.2: Uncertain augmented pitch actuator-WT model.

### 4.3 Fault in the Pitch Actuator

In the previous modeling approach, the actuator model (4-4) is assumed exactly known. However, it has been shown in the literature that WT’s pitch actuator is frequently subjected to different faults [72]. Therefore, the general second order linear model of the pitch actuator (4-7) is incorporated into the CART3’s synthesis and simulation models [99]:

![Diagram](image3)
\[ \beta = \frac{\omega_n^2}{s^2 + 2\xi\omega_n s + \omega_n^2} u, \quad (4-7) \]

where the values for the damping ratio \( \xi \) and natural frequency \( \omega_n \) of the actuator are provided in Table 4.2 for no fault and faulty conditions. It can be seen that both \( \xi \) and \( \omega_n \) vary depending on the type of fault [40]. Step responses from the control command signal \( u \) to the actual pitch angle \( \beta \) are shown in Fig. 4.3 for the different cases outlined in Table 4.2. These responses clearly show that the faulty actuator has slower dynamics than the one with no fault.

<table>
<thead>
<tr>
<th>Table 4.2: Fault parameters for the second order actuator model of the turbine.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Actuator condition</strong></td>
</tr>
<tr>
<td>High air content in the oil</td>
</tr>
<tr>
<td>Pump wear</td>
</tr>
<tr>
<td>Hydraulic leakage</td>
</tr>
<tr>
<td>Pressure drop (low pressure)</td>
</tr>
</tbody>
</table>

Fig. 4.3: Step responses of different actuator models given the parameters in Table 4.2

In robust control, it is preferred to combine different uncertainties in order to have the fewest possible uncertain parameters. This provides a less conservative design. Although it does not result in an exact model, motivated by [39] and [40] to combine the vertices of the given parameters in Table 4.2, a convex approximation is achieved in order to relate the changes in \( \xi \) and \( \omega_n \) to a single fault parameter \( \theta_f \) as (4-8) and (4-9):

\[ \omega_n^2(\theta_f) = \omega_{n,0}^2 + (-\omega_{n,0}^2 + \omega_{n,lp}^2)\theta_f, \quad (4-8) \]

\[ \xi\omega_n(\theta_f) = \xi_0\omega_{n,0} + \left(-\xi_0\omega_{n,0} + \xi_{n,lp}\omega_{n,lp}\right)\theta_f, \quad (4-9) \]
where \( \xi_0 \) and \( \omega_{n,0} \) are the damping ratio and natural frequency of the fault free model, \( \xi_{n,lp} \) and \( \omega_{n,lp} \) are the parameters of the actuator with low pressure fault, and \( \theta_f \in [0,1] \). This results in an augmented actuator-WT model as (4-10):

\[
\begin{align*}
\dot{x} &= A(\theta_f)x + B(\theta_f)u + B_d u_d \\
y &= Cx
\end{align*}
\]  

(4-10)

where,

\[
A(\theta_f) = A_0^f + A_1^f \theta_f \\
B(\theta_f) = B_0^f + B_1^f \theta_f \\
B_d(\theta_f) = B_{d,0}^f
\]

Then, \( \theta_f = \bar{\theta}_f(1 + p_f \delta_f) \) will be used for active robust control design with respect to the parametric uncertainty in the fault parameter. In this model, \( \bar{\theta}_f \) is the nominal fault parameter for any local model, \( \theta_f \) is the corresponding uncertain fault parameter, \( p_f \) is the uncertainty weight and \( |\delta_f| \leq 1 \) is the real-valued fault uncertainty. Fig. 4.4 shows the block diagram of the augmented actuator-WT model for the purpose of robust control design. It should be noted that “nominal” model is obtained for \( \theta_f = \bar{\theta}_f \) when \( p_f = 0 \), which is different from the “no fault” model where \( \theta_f = 0 \).

![Block Diagram](image)

Fig. 4.4: Uncertain augmented pitch actuator-WT model with complex-valued unmodeled dynamics uncertainty \( \Delta \) and real-valued fault uncertainty \( \delta_f \).

The generalized plant can be represented in state space form of (4-11) useful for robust FTC design:

\[
\begin{align*}
\dot{x} &= Ax + B_1 u_f + B_{u,2} u + B_{d,2} u_d \\
y_f &= C_1 x + D_{11} u_f + D_{u,12} u + D_{d,12} u_d \\
y &= C_2 x + D_{21} u_f + D_{u,22} u + D_{d,22} u_d
\end{align*}
\]  

(4-11)

4.4. Wind-Dependent Behavior of Wind Turbines

To model the wind-dependent nature of WT dynamics, the FAST code is programmed to obtain 11 LTI models of CART3 for wind speeds ranging from 14 to 24 m/s (the linearization is done every 1 m/s in region 3, where the pitch actuator should be utilized to control the WT). As
shown in Fig. 4.5, the locations of the poles of CART3’s LTI model (4-3) change depending on the wind speed. As can be seen, these locations significantly move to the left by any increase in the wind speed. Also, Fig. 4.6 depicts the change in the normalized bandwidth $BW = \frac{BW_{at\ given\ u_d}}{BW_{at\ 14\ m/s}}$ from the collective pitch angle input to the generator speed output. In general, this indicates that a better control authority is available at higher wind speeds comparing to the lower ones.

![Fig. 4.5: Change in pole locations of CART3 by wind speed (Red: 14 m/s and Blue: 24 m/s).](image)

![Fig. 4.6: Change in BW by wind speed.](image)

### 4.5. Wind-Dependent Model of Wind Turbines

In order to have a wind-scheduled robust controller for WTs, the LTI model (4-3) has to be extended into a wind-dependent model. To do this, a wind-dependent pattern can be defined for the $A, B$ and $B_d$ system matrices of (4-3) in order to capture the wind-dependent behavior of the
WT at the modeling stage. Without loss of generality, it is assumed that the $A$, $B$ and $B_d$ matrices linearly depend on the wind speed, as shown in (4-12)-(4-14).

$$A(\theta_{ud}) = A_0^d + A_1^d \theta_{ud}$$

(4-12)

$$B(\theta_{ud}) = B_0^d + B_1^d \theta_{ud}$$

(4-13)

$$B_d(\theta_{ud}) = B_{d,0}^d + B_{d,1}^d \theta_{ud}$$

(4-14)

Then, 11 linear models of CART3 in region 3 are used to find the approximated system matrices (e.g., $A_0^d$ and $A_1^d$). Therefore, the wind-dependent model is defined to be as (4-15).

$$\begin{aligned}
\dot{x} &= A(\theta_{ud})x + B(\theta_{ud})u + B_d(\theta_{ud})u_d \\
y &= Cx
\end{aligned}$$

(4-15)

where $\theta_{ud} = u_d$ but a new notation is used to show the difference between wind disturbance input $u_d$ and modeling parametric uncertainty due to the wind, i.e. $\theta_{ud}$.

Remark: While it is straightforward to use higher order terms and have a better approximation of the system matrices (e.g., $A(\theta) = A_0^d + A_1^d \theta + A_2^d \theta^2$), the 1st order wind-dependent approximations (4-12)-(4-14) are believed to be adequate for capturing the wind-dependent behavior of WTs. This helps simplify the final robust control synthesis. To compensate the possible effects of this mismatch, the gain $k_{wt}$ of the uncertainty weight $w_{wt}$ in equation (4-6) is increased appropriately.

Because the design is intended for region 3, it is assumed that $\theta_{ud} \in [14,24]$ m/s. Then, $\theta_{ud} = \bar{\theta}_{ud} (1 + p_{ud} \delta_{ud})$ will be used for active robust control design with respect to the wind-dependent parametric uncertainty. Here, $\bar{\theta}_{ud}$ is the nominal local wind speed and $\theta_{ud}$ is the uncertain one. Also, $p_{ud}$ is the uncertainty weight over the given wind speed local interval, and $|\delta_{ud}| \leq 1$ is a real-valued scalar uncertainty. It is important to note that $p_{ud} = 0$ gives the “nominal model” of $\theta_{ud} = \bar{\theta}_{ud}$ whereas $p_{ud} \neq 0$ represents the existence of uncertainty in model.

Fig. 4.7 shows the block diagram of this WT model representation.
4.6. Wind-Dependent Model of Wind Turbines with Fault in the Pitch Actuator

In this case, the model of the augmented actuator-WT is given as in (4-16).

\[
\begin{align*}
\dot{x} &= A(\theta_{u_d}, \theta_f)x + B(\theta_{u_d}, \theta_f)u + B_d(\theta_{u_d})u_d, \\
y &= Cx,
\end{align*}
\]  

(4-16)

where,

\[
A(\theta_{u_d}, \theta_f) = A_0^{df} + A_1^{df} \theta_{u_d} + A_1^{df} \theta_f,
\]

\[
B(\theta_{u_d}, \theta_f) = B_0^{df} + B_1^{df} \theta_{u_d} + B_1^{df} \theta_f,
\]

\[
B_d(\theta_{u_d}, \theta_f) = B_{d,0}^{df} + B_{d,1}^{df} \theta_{u_d}.
\]

The approximated system matrices can be easily obtained from the previous analysis. The uncertain model of the WT with respect to unmodeled dynamics, pitch actuator fault, and wind-dependent linear model is depicted in Fig. 4.8.

Fig. 4.8: Uncertain wind-dependent model of the augmented actuator-WT with fault in actuator. The complex-valued unmodeled dynamics uncertainty \( \Delta \), real-valued wind-dependent uncertainty \( \delta_{u_d} \) and real-valued fault uncertainty \( \delta_f \) are separately addressed in this approach.
CHAPTER 5
ACTIVE FAULT TOLERANT PITCH CONTROL OF WIND TURBINES

This chapter develops the generalized plant $P(s)$ for the purpose of FTC design and applies the DK-iteration discussed in Chapter 3 to design the local controllers. Then, active robust control theory of Chapter 3 is used to design a global FTC for the WT application. First, the general design procedure for the pitch actuator FTC is explained. Design steps are then discussed in more detail. Finally, simulation results are provided to verify the feasibility of the proposed idea for the WT application.

5.1. Pitch Actuator FTC; Design Procedure

The general idea is to use the fault parameter $\theta_f$ as an uncertain parameter, and design a set of local robust controllers for different overlapping intervals. Then, the mixing approach is implemented to determine the global control signal $u$ that should be sent to the pitch actuator. The design procedure for active robust fault tolerant pitch control is as follows:

1. Find the LTI model of the WT, choose an acceptable order for the model as “nominal model”. Then, augment the nominal model with the fault parameter-dependent actuator model.

2. Assume the fault parameter $\theta_f$ is the uncertain varying parameter in the model that changes from $\theta_{f,min} = 0$ for nominal fault to $\theta_{f,max} = 1$ for low pressure cases (extreme case).

3. Determine a robust synthesis configuration for the FTC problem. As a guideline for determining a performance parameter used to select the number of required models, consider the wind speed disturbance to be an unwanted external input. Its effect on regulated speed should be as small as possible for all actuator conditions. Here, this performance criterion is based on the disturbance rejection property of the fault tolerant pitch controller. In other words, this configuration makes it possible to define a performance criterion $C_f$ that can be used to determine the length of each local $\theta_f$ interval (uncertain parameter) systematically (steps 4-5).

4. First, an upper limit for the design should be determined. This represents the best possible performance.
4.1. Start with the LTI model for the case $\theta_f = \theta_{f,\text{min}}$. Design a robust controller with acceptable stability and performance (in the current design, this is determined based on peak $- \mu$ value). Then, name the corresponding $C_f$ as $C_f^{1*}$ where “1” stands for the number of the local FTC and * denotes that there is no uncertainty in $\theta_f$.

4.2. Determine an acceptable resolution $\epsilon_{\theta_f}$ as the step size to have a set of high resolution performance criteria. Redo Step 4.1 for $\theta_{f,i}^{i*} = \theta_{f,\text{min}} + i \times \epsilon_{\theta_f}$ where $i = 1,2,...,N$ and $N$ is determined based on the step size and the length of the parameter interval $\theta_{f,i}^{i*} \in [\theta_{f,\text{min}}, \theta_{f,\text{max}}] = [0,1]$ (for example, if $\epsilon_{\theta_f} = 0.1$, then $N = 10$). If the resulting performance is $C_f^{i*}$, then there will be a table of performance criteria $C_f^{i*}$ versus $\theta_{f,i}^{i*}$ as the maximum achievable performance for each $\theta_{f,i}^{i*}$. In order to provide guarantees for continuous changes in the fault parameter, an infinite number of these point-wise controllers is required. Since this is impossible to implement, a new set of controllers should be designed as discussed in Step 5.

5. At this step, an acceptable number of robust controllers should be synthesized to replace the large number of point-wise controllers designed at Step 4. Assume there is an uncertainty in $\theta_f$, and design a more realistic second set of controllers that will be implemented in simulation.

5.1. To do this, in synthesis, set $C_f^j = k C_f^{1*}$ where $k \leq 1$ is a design parameter which indicates the minimum acceptable performance for the closed-loop system. Then, increase the length of the first uncertain interval $[\theta_{f,\text{min}}, \theta_{f,1}]$ to synthesize a robust controller for this interval.

5.2. Then, starting from $\theta_{f,1}$, follow the same procedure up to the $\theta_{f,\text{max}}$.

5.3. As the fault parameter goes from $\theta_{f,\text{min}}$ to $\theta_{f,\text{max}}$, the control objective should change from maximum wind speed disturbance rejection to maximum lifetime for the actuator. Therefore, when moving to the next interval, decrease $C_f^j$ for $j^{th}$ local robust controller. As a result, the effect of the actuator weighting function $W_a$ is increased in the design procedure such that in faulty cases the controller will use the actuator less than in the no-fault case.
6. Finally, measure the uncertainty parameter $\theta_f$ in order to appropriately weigh different controllers in such a way that the overall FTC shows good transient behavior when switching from one local FTC to the next.

5.2. Design of Local Robust Fault Tolerant Pitch Controller

The general idea, design issues and the tradeoff in frequency domain are explained in Chapter 3. In this Section, more details are provided regarding the design of local robust controllers based on the proposed steps in Section 5.1.

Steps 1 and 2 are discussed in Section 4.3, and will not be elaborated here. For Step 3, a synthesis configuration should be determined considering the design criteria of Section 3.3.1. Having the definitions provided at Section 3.3.2, a mixed $S/T/SK$ performance criterion is proposed for the norm-minimization problem in robust control. This performance output vector, if designed correctly, would ensure good reference tracking, disturbance rejection and robust stabilization with respect to all types of uncertainties in the augmented plant of Fig. 4.4. Additionally, the term $SK$ helps achieve the previous goals with optimum control effort at each frequency. This happens through correct selection of different weighting functions as is shown in Fig. 5.1. A comprehensive guideline for weighting function selection can be found in [74], [89] and [100]-[102].

![Fig. 5.1: Closed-loop form of the proposed robust control structure.](image)

The final weighting functions for the WT control problem are selected as follows:

1. Due to the importance of generator speed regulation at low frequencies and the fact that wind speed is a low frequency signal (see Fig. 5.2), the performance weighting function $W_p$ is selected as a low pass filter to generate the weighted reference tracking error signal $z_p$. 
2. $W_T$ helps control the bandwidth of the system and weigh the measured generator speed (this is different from the tracking error). In the current work, this is used to control the locations of the zeros of the system in order to reduce the overshoot during transient response to the changes in wind speed disturbance.

3. $W_u$ function penalizes the actuator usage and, in general, is a mean to incorporate the actuator saturation limits into the problem.

4. $M_{zh}$ is an additional block which enables designing a robust controller with integral action property [89]. This helps achieve a better generator speed regulation in region 3 of WT operation.

In order to use the proposed strategy for a WT application, it is required to scale the WT model such that the 2-norm of external signals vector becomes equal to unity. Having such a scaled model, the weighting function $W_d$ is a shaping function in frequency domain that models the wind speed disturbance. This results in the generalized plant of Fig. 5.3 for which a controller $K$ should be designed to stabilize the closed-loop system. With no modeling uncertainty, this problem can be viewed as a standard $H_\infty$ optimization where $w = [d, r]^T$ and $z = [z_p, z_T, z_u]^T$ are external signal and performance output vectors, respectively. However, the problem can be changed to a non-standard $H_\infty$ optimization (robust performance problem) if the uncertainty in modeling is added in order to find a stabilizing controller $K$ for which $\|T_{zw}\|_\infty \leq 1 \forall \{\omega \text{ and } \Delta_{DK}\|\Delta_{DK}\|_\infty \leq 1\}$, where $T_{zw}$ is transfer function from $w$ to $z$. $\Delta_{DK}$ block is defined in Chapter 3 where the structured modeling uncertainty block is defined to be as follows for the FTC design:

$$\Delta l = \begin{bmatrix} \delta_f & 0 \\ 0 & \Delta \end{bmatrix}.$$
Fig. 5.3: Open-loop structure should be used to find the generalized plant $P(s)$. The uncertainty blocks are removed and the controller needs to be designed (all these blocks are shown with dashed red lines).

This robust performance problem can be solved by mixed $\mu$ robust control approach as given by Fig. 5.4. Further information about external signal vector and performance output selection for robust performance problem is available in [74] and is not detailed here.

Fig. 5.4: Required configuration to design local FTCs. The generalized plant $P(s)$ includes the weighting functions, WT and the actuator models.

For the open-loop structure of Fig. 5.3, the weighting functions are as follows:

$$W_d = C_d \frac{0.3}{s+0.3},$$
where $C_d, C_{W_p}, C_{W_T}$ and $C_u$ are the constant gains for the design of all local controllers. $C_f$ is the performance parameter which is also included in the $W_T$ function. This modification, helps control the location of the system’s zeros appropriately. Also, $\alpha$ is a positive number that provides the required integral action.

For Step 4, with no parametric uncertainty in fault parameter $\theta_f$, solving the robust performance problem with the mixed $\mu$ design approach would lead to Table 5.1 as the upper bounds on the performance (some sample point-wise designs are given here). In all cases, the peak $\mu$ value is around 0.99 to ensure both robust stability and robust performance of the closed-loop system.

<table>
<thead>
<tr>
<th>$\theta_f$</th>
<th>0.0</th>
<th>0.2</th>
<th>0.4</th>
<th>0.6</th>
<th>0.8</th>
<th>1.0</th>
</tr>
</thead>
<tbody>
<tr>
<td>$C_f$</td>
<td>1</td>
<td>0.995</td>
<td>0.984</td>
<td>0.965</td>
<td>0.940</td>
<td>0.80</td>
</tr>
</tbody>
</table>

Step 5 is summarized in Table 5.2. Here, the lengths of the overlaps in the $\theta_f$ intervals are obtained by trial and error in order to achieve the best possible simulation results considering the maximum precision of fault estimator. However, each interval’s length is determined with the help of mixed $-\mu$ design algorithm such that the peak $\mu$ values remain around 0.99 for all cases, for closed-loop robust stability and performance. Additionally, the order of each local controller was originally designed to be around 23, which is high and may therefore lead to implementation difficulties. Therefore, an order reduction technique is applied to reduce the order of all controllers to 8 or 9, as indicated in Table 5.2 (see [89] for detailed information about order reduction methods based on Hankel norm of the high-order system). Figure 5.5 shows that the reduced order controller has a similar bode magnitude plot as that of the full order controller for the 16th local robust design. Additionally, it can be seen that the controller has the desired integral action at low frequencies.
Table 5.2: Local robust FTCs

<table>
<thead>
<tr>
<th># of controller</th>
<th>$\theta_f$</th>
<th>$C_f$</th>
<th>$\text{peak} - \mu$</th>
<th>Reduced order</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>[0.000,0.150]</td>
<td>0.700</td>
<td>0.987</td>
<td>9</td>
</tr>
<tr>
<td>2</td>
<td>[0.120,0.240]</td>
<td>0.696</td>
<td>0.988</td>
<td>9</td>
</tr>
<tr>
<td>3</td>
<td>[0.210,0.320]</td>
<td>0.696</td>
<td>0.989</td>
<td>9</td>
</tr>
<tr>
<td>4</td>
<td>[0.300,0.400]</td>
<td>0.696</td>
<td>0.988</td>
<td>9</td>
</tr>
<tr>
<td>5</td>
<td>[0.380,0.475]</td>
<td>0.688</td>
<td>0.989</td>
<td>9</td>
</tr>
<tr>
<td>6</td>
<td>[0.460,0.545]</td>
<td>0.686</td>
<td>0.986</td>
<td>9</td>
</tr>
<tr>
<td>7</td>
<td>[0.530,0.610]</td>
<td>0.680</td>
<td>0.991</td>
<td>9</td>
</tr>
<tr>
<td>8</td>
<td>[0.600,0.670]</td>
<td>0.675</td>
<td>0.984</td>
<td>8</td>
</tr>
<tr>
<td>9</td>
<td>[0.660,0.720]</td>
<td>0.675</td>
<td>0.976</td>
<td>8</td>
</tr>
<tr>
<td>10</td>
<td>[0.715,0.775]</td>
<td>0.664</td>
<td>0.994</td>
<td>8</td>
</tr>
<tr>
<td>11</td>
<td>[0.770,0.820]</td>
<td>0.660</td>
<td>0.984</td>
<td>8</td>
</tr>
<tr>
<td>12</td>
<td>[0.815,0.860]</td>
<td>0.651</td>
<td>0.982</td>
<td>8</td>
</tr>
<tr>
<td>13</td>
<td>[0.855,0.895]</td>
<td>0.645</td>
<td>0.981</td>
<td>8</td>
</tr>
<tr>
<td>14</td>
<td>[0.890,0.930]</td>
<td>0.630</td>
<td>0.998</td>
<td>8</td>
</tr>
<tr>
<td>15</td>
<td>[0.925,0.965]</td>
<td>0.568</td>
<td>0.995</td>
<td>8</td>
</tr>
<tr>
<td>16</td>
<td>[0.960,1.000]</td>
<td>0.546</td>
<td>0.994</td>
<td>8</td>
</tr>
</tbody>
</table>

Fig. 5.5: Bode magnitude plot comparison of the full order and reduced order models for the 16th local controller. For reference tracking purposes, the controller shows the required integral action property at low frequencies.
For Step 6, the mixing approach (3-11) and (3-12) is used for $N = 16$. As an example, the 3rd mixing function is $F(\theta_f, 0.21, 0.24, 0.30, 0.32)$.

Finally, the block diagram of the closed-loop system is shown in Fig. 5.6, where $u$ is the control command and fault estimator (FE) stands for the fault estimator block (which provides the estimation of the fault parameter $\theta_f$). It is assumed that the estimation provided by FE is precise in such a way that the estimated fault parameter $\hat{\theta}_f$ is the same as the actual one. Thus, for this research, the fault parameter $\theta_f$ is directly sent to the control block.

![Block Diagram of the Closed-Loop System](image)

**Fig. 5.6: Closed-loop wind energy conversion system with FTC.**

### 5.3. Simulation Verification

In this section, the FTC with mixing is implemented in Simulink to control the nonlinear model of CART3 modeled by FAST code and augmented with a second order pitch actuator as shown in Fig. 5.6. The other control inputs in FAST model, i.e. generator torque and yaw angle, are kept constant at their rated values. The control objective is to regulate the generator speed, which is a measured signal, to its rated value of 1800 rpm in the presence of the turbulent wind disturbance and in spite of possible faults in the pitch actuator. This regulation is accomplished by collectively pitching the blades while the pitch actuator signals are ensured to never exceed their limits. For CART3, the pitch angle, rate and acceleration should stay within the ranges of $[0, 20]$ deg., $[-18, 18]$ deg./s, and $[-150, 150]$ deg./s$^2$ for normal operation respectively [103]. However, in this work, pitch rate is limited to 3 deg./s in the simulations in order to take care of any possible mismatches in implementation.

Simulation results of the closed-loop system equipped with FTC with mixing are shown in Fig. 5.7. Here, the top subplot shows the hub-height wind speed, which is within region 3. This
wind input has a mean speed of 18 m/s and 12.20% turbulence intensity. The fault scenario is shown in the second subplot, where $\theta_f = 0$ refers to no fault condition and $\theta_f = 1$ stands for low pressure in the pitch actuator (see Table 4.2). The third subplot identifies the number of the controller that is active at each time. Note that on a boundary around the step times, the mixing approach keeps two adjacent local controllers active, which is not shown in Fig. 5.7. The bottom subplot confirms that the proposed controller is able to regulate the generator speed around its rated value in spite of the faulty actuator. Moreover, the regulation performance is similar for both faulty and no fault cases. Also, as was identified as one of the control objective, smooth transition enabled by the adopted mixing strategy is apparent as there are no transient spikes in the controlled signal.

![Simulation results of FTC with mixing.](image)

Pitch actuation signals for the faults in the actuator and the proposed FTC method are presented in Fig. 5.8. As is clearly visible in the pitch acceleration signal, during the fault (200-275 s) the FTC uses the actuator less than when there is no fault (50-100 s and 375-450 s) as it tries to keep the turbine operating. For all signals, even the pitch acceleration, there is no
transient spike when changing the local controllers. Moreover, all signals are within their allowable limits.

Although the proposed FTC provides no guarantees on component loads, Fig. 5.9 and Fig. 5.10 show that the controller causes no unusual mechanical loads on turbine components during fault times.

Fig. 5.8: Actuator signals of FTC with mixing.
Fig. 5.9: Tower fore-aft acceleration (top) and tower side-to-side acceleration (bottom) for the given fault scenario.

Fig. 5.10: Blade 1 moments for the given fault scenario.
CHAPTER 6
WIND-DEPENDENT ACTIVE FAULT TOLERANT PITCH CONTROL OF WIND TURBINES

In this chapter, an alternative approach for direct LIDAR-based control of WTs is proposed based on the concept of active robust control. The first part of this chapter establishes the requirements for designing a wind-dependent robust controller while considering the wind-dependent behavior of WT model. Then, the design is generalized to synthesize a wind-dependent fault tolerant pitch controller for wind turbines in region 3. The feasibility of these designs is tested through simulations.

6.1. Wind-Dependent Active Robust Controller

Until now, to the best of the author’s knowledge, [63] has been the only reference that discusses the effect of the inaccuracy in LIDAR measurement on the closed-loop performance of the direct LIDAR-based control strategies. In the current research, the indirect LIDAR-based WT control idea is introduced that considers the unmodeled dynamics uncertainty, wind-dependent behavior of linear model of WTs, as well as wind disturbance rejection on regulated signal and LIDAR measurement inaccuracy.

As depicted in Fig. 6.1, the proposed indirect LIDAR-based control idea has a feedback control structure. The properties of the controller can be adjusted based on the LIDAR measurements (e.g., wind speed, shear, gust and turbulence intensity) so that it is able to efficiently operate over a range of wind speeds. Although gain scheduling or LPV techniques could be utilized here, active robust control strategy in general is proven to have more flexibility compared to these techniques, and can therefore achieve the intended design goals more efficiently. In essence, by designing different local controllers it is possible to have different weighting functions for each local wind speed range; hence, the properties of the controller can be adjusted based on the scheduling signal value. Also, through the use of a mixing strategy, the controller generates a global control signal that is robust against a certain level of inaccuracy in the LIDAR measurements.
6.1.1. Wind-Dependent Controller; Design Procedure

The general idea adopted here is similar to the FTC system; however, different from the latter, the local controllers here should be robust with respect to changes in wind parameter $\theta_{u_d}$ measured by LIDAR. In addition, a different set of weighting functions is used for each local controller in order to achieve different properties based on the local linear model of the WT (see Section 4.4). In the FTC design, the overlap between local controllers was used to provide smooth transition from one controller to the adjacent one. Here, with no additional complexity, this overlap is viewed as a design parameter that provides robustness with respect to inaccuracies in wind speed measurement. The procedure is summarized as follows:

1. Find the wind-dependent model of the WT with an acceptable order. Then, augment this model with the ideal actuator model.

2. Assume the wind parameter $\theta_{u_d}$ is the uncertain parameter in the model that changes from $\theta_{u_d,\min} = 14 \text{ m/s} \text{ (as the rated wind speed)}$ to $\theta_{u_d,\max} = 24 \text{ m/s} \text{ (as the cutout wind speed)}$. This interval defines region 3 of WT operation.

3. Determine a robust synthesis configuration for the wind-dependent design problem. This structure must be flexible to use the knowledge on the wind-dependent behavior of the system.

4. Start from one side of the $\theta_{u_d}$-interval (e.g., $\theta_{u_d,\max}^{\max}$) and design a locally robust controller for the first interval with the length of $\alpha_1$ (i.e., $[24, 24 - \alpha_1]$).

5. Consider an overlap with the length of $\varepsilon$ to have a level of robustness with respect to the inaccuracy in wind speed measurement and redo step#3 to design other local controllers up to the other end of the $\theta_{u_d}$-interval (the second interval could be $[24 - \alpha_1 + \varepsilon - \alpha_2, 24 - \alpha_1 + \varepsilon]$).
6. Measure the wind speed by LIDAR and use the mixing strategy to schedule the local controllers and generate the final global control signal.

Remark: In this approach, it is not possible to find an upper bound on performance similar to what was done in the FTC method. This is because here all the weighting functions need to be changed based on the local wind speed interval. Therefore, the gain of $W_p$ can no longer be used as a performance parameter for the local intervals.

6.1.2. Design of Local Robust Wind-Dependent Pitch Controller

Steps 1 and 2 are elaborated in Chapter 3, and will not be repeated here. For Step 3, the main objectives, and the required structure for achieving those objectives, are similar to those of FTC synthesis for an open-loop configuration as in Fig. 6.2. This block diagram is used in Fig. 6.3 in order to design a mixed $\mu$ robust controller where $\Delta_p$ is a fictitious performance uncertainty block and $\Delta_l$ is the modeling uncertainty block:

$$\Delta_l = \begin{bmatrix} \delta_{ud} & 0 \\ 0 & \Delta \end{bmatrix}.$$

Based on the analysis for wind-dependent behavior of WTs, the key idea is to change the weighting functions according to the nominal local wind speed:

$$W_d = C_d \frac{0.3}{s + 0.3},$$

$$W_p = C_p(\bar{\theta}_{ud})C_{Wp} \frac{s + l_p(\bar{\theta}_{ud})}{s^2 + 1.02s + 0.02},$$

$$W_t = C_p(\bar{\theta}_{ud})C_{Wt} \frac{s + l_t(\bar{\theta}_{ud})}{s^2 + 1.02s + 0.02},$$

$$W_u = C_u,$$

$$W_{wt} = C_{wt} \frac{0.17s + 0.01}{0.015 + 1},$$

$$M_{zh} = \frac{s + \alpha}{s}.$$

where $C_d$, $C_{Wp}$, $C_{Wt}$, $C_u$, $C_{wt}$ and $\alpha$ are assumed constant numbers for the synthesis of all local controllers. Since the control objectives have a unique interpretation in the frequency domain, it is possible to relate the weighting functions to nominal wind speed (i.e., $\bar{\theta}_{ud}$) as in $C_p(\bar{\theta}_{ud}), l_p(\bar{\theta}_{ud}), l_t(\bar{\theta}_{ud})$ and $l_{d}(\bar{\theta}_{ud})$. These functions are carefully determined to have specific closed-loop properties for each local interval, based on the guidelines discussed in robust control literature (e.g., [74], [89] and [100]-[102]).
Fig. 6.2: Open-loop structure for wind-dependent design. The controller should be designed with the uncertainty blocks removed (all these blocks are indicated with dashed red lines). This configuration is used to find the generalized plant $P(s)$.

Fig. 6.3: Required configuration to find the local wind-dependent controllers via DK-algorithm. Generalized plant $P(s)$ includes the weighting functions, WT and the actuator models.

Steps 4 and 5 are summarized in Table 6.1 where the order of original local controllers was initially in the range of 29 to 31, which was then reduced to the range of 12-15 through order reduction techniques.
Table 6.1: Local robust controllers for wind-dependent design.

<table>
<thead>
<tr>
<th># of controller</th>
<th>$\theta_{ud}$ (m/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>[20, 24]</td>
</tr>
<tr>
<td>2</td>
<td>[17.5, 21.5]</td>
</tr>
<tr>
<td>3</td>
<td>[15, 19]</td>
</tr>
<tr>
<td>4</td>
<td>[14, 16.5]</td>
</tr>
</tbody>
</table>

6.1.3. Robustness with respect to LIDAR Measurement Inaccuracy

The block diagram of closed-loop system is provided in Fig. 6.4, where $u$ represents the control command and $d$ stands for wind disturbance. LIDAR measures the wind speed $u_d$ and passes it through a filtering block first in order to generate $u_d^f$ as a smooth estimation for wind parameter $\theta_{ud}$ that would be used as the scheduling signal. This block filters out the unnecessary high frequency components of LIDAR measurement. However, as a result of this, the actual wind speed on the hub can be different from the filtered measurement. This may lead to an incorrect weighting of the local controllers in the mixing approach. Therefore, it is highly desirable to consider this measurement error in the design of the global controller.

In the mixing approach, there is an overlap between the mixing functions that, originally, was designed to provide a smooth and stable transition between local controllers. However, this can serve as a means to help deliver robustness with respect to some level of inaccuracies in the measured wind speed. In Fig. 6.5 this is graphically shown for a typical wind speed, and assuming two local controllers $K_1$ and $K_2$ that correspond to the weighting functions $F_1$ and $F_2$. $K_1$ is robust over the range $\theta_{ud} \in [\theta_1, \theta_4]$ and $K_2$ is robust over $\theta_{ud} \in [\theta_3, \theta_6]$. Under worst case conditions, the actual wind speed that hits the blade could be close to the overlap of the two (e.g., $\theta_3$). As long as $K_1$ is the controller within the loop, the stability and performance of the closed-
loop system is guaranteed by the proposed active robust controller. For this example, the overlaps are assumed to be of the same length. Hence, the maximum allowable wind measurement error should be $\theta_4 - \theta_3$. However, not all this range is useful because the weight $F_1$ goes to zero when $\theta$ gets close to $\theta_4$; therefore, $k \in [0,1)$ is used as a design parameter that determines $k \times (\theta_4 - \theta_3)$ m/s as the guarantee level. On the other hand, the best case scenario would happen when the wind speed lies within the overlap $\theta_{ud} \in [\theta_3, \theta_4]$. In this case, the measured signal is allowed to fall anywhere in the range of $\theta_{ud} \in [\theta_1, \theta_6]$.

![Weight](image)

Fig. 6.5: Using the overlap to provide robustness with respect to the LIDAR inaccuracy. The actual (solid red line) and measured (dashed red curve) wind speed parameters are drawn for the worst case scenario.

Because of low pass filtering behavior of the turbine’s rotor, the high frequency components of wind profile do not change the general properties of the LTI model of WTs. In other words, the analysis of Section 4.4 is only valid for steady state wind speed signals. Considering the estimated hub height wind speed and in the view of a low pass filtered wind speed due to rotor’s effect, the maximum effective wind speed error associated with the dynamics of CART3 is around 1 m/s for the wind speed profile used in this thesis. It is emphasized that this analysis is only valid for indirect LIDAR-based controller, CART3, the given wind profile, and with the special LIDAR configuration.
6.1.4. Simulation Verification

The simulation is performed for a wind profile with a mean speed of 18 m/s and a high turbulence intensity of 12.2% that stays within region 3 at all times. The generator speed signals for closed-loop CART3 system are illustrated in Fig. 6.6 for two cases, when controlled with CART3’s PI baseline controller (BLC) and when controlled with the proposed indirect LIDAR-based controller. As shown in the figure, the new approach outperforms the BLC in terms of generator speed regulation. Also, the pitch angle signals required by these controllers are depicted in top subplot of Fig. 6.7. These are close to one another since both controllers show integral action at low frequencies. However, the differences are increased for rate and acceleration signals because of the differences in the bandwidths of the proposed controller and the BLC.

![Wind speed and generator speed plots](image)

**Fig. 6.6:** Generator speed regulation with BLC (blue) and LIDAR-based (red) controllers.

The results of 550 seconds of simulation are used to provide numerical verification. In the following cases, the level of improvement by the new method is denoted by a positive number compared to the performance of BLC. This analysis is summarized in Table 6.2 based on root-mean-square (RMS) and damage equivalent load (DEL) for different signals. DEL analysis is described in [104]. Although the general performance is acceptable because of the high level of improvement in power regulation and tower load, there are instances that some loads are
increased due to the effect of the controller’s frequency shape on the unmodeled dynamics. This will be further discussed in the future work section of the thesis.

![Graphs](image)

Fig. 6.7: Required pitch actuation signals for the given wind file by BLC (blue) and LIDAR-based (red) controllers.

<table>
<thead>
<tr>
<th>Performance</th>
<th>% of Improvement</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMS error of power regulation</td>
<td>35.5</td>
</tr>
<tr>
<td>DEL on tower fore-aft moment</td>
<td>10</td>
</tr>
<tr>
<td>DEL on low speed shaft torque</td>
<td>8.5</td>
</tr>
<tr>
<td>DEL on rotor flapwise moment</td>
<td>-2</td>
</tr>
</tbody>
</table>

### 6.2. Wind-Dependent Active Robust Fault Tolerant Pitch Controller

This section combines the idea of wind-dependent controller with the FTC in order to present a 2-dimentional design.

#### 6.2.1. Wind-dependent controller design procedure

1. Find the wind-dependent model of WT with unstructured dynamics uncertainty and presence of faults in the pitch actuator. Assume $\theta_{ud} = [\theta_{ud}^{min}, \theta_{ud}^{max}] = [14, 24]$ m/s and $\theta_f = [\theta_f^{min}, \theta_f^{max}] = [0, 1]$ are the uncertain parameters with respect to which the controller should be robust.
2. Determine a robust design structure with appropriate performance output vector along with the design objectives. Considering the analysis for wind-dependent behavior of WTs and the fault-dependent behavior of the actuator, this configuration should be flexible to use the knowledge on linear model of WT.

3. To have an implementable 2-dimensional mixing function, simplify the design and predetermine an appropriate range for $\theta_{ud}$ local intervals. This knowledge can be obtained from the wind-dependent controller design described previously. Fix this interval length and find the length of the $\theta_f$ interval accordingly. In this research, the length of the $\theta_f$ intervals is also considered fixed which means the local controllers are implemented based on the scheme depicted in Fig. 6.8. As a result, $mn$ locally robust controllers should be designed.

4. Measure the wind speed by LIDAR and the fault parameter by the fault estimator, use a 2-dimensional mixing strategy to weigh the local controllers and generate the final global control signal.

![Fig. 6.8: Localization of the wind-dependent active robust FTC. The length of all intervals are predetermined and fixed.](image)

6.2.2. Design of Local Robust Wind-Dependent Fault Tolerant Pitch Controllers

In this design, the synthesis configuration is similar to the previous cases, but this time with two parametric uncertainties. This is shown as the open-loop structure of Fig. 6.9 where the weighting functions are determined based on the available knowledge about the wind-dependent behavior and the fault condition of the WT for each local interval. Based on this scheme, the generalized plant $P(s)$ can be used in DK-algorithm as is shown in Fig. 6.10. Then, the DK-
Algorithm can be used to find each local controller assuming the following structured uncertainty block:

\[
\Delta l = \begin{bmatrix}
\delta_{u_d} & 0 & 0 \\
0 & \delta_f & 0 \\
0 & 0 & \Delta
\end{bmatrix}
\]

Fig. 6.9: Open-loop structure for wind-dependent design. The controller needs to be designed with uncertainty blocks removed (all these blocks are indicated by dashed red lines). The generalized plant should be generated from this figure.

Fig. 6.10: Generalized plant for local wind-dependent active robust FTC synthesis.
6.2.3. 2-Dimensional Mixing of the Local Controllers

For the mixing strategy, the formulation is the same as the wind-dependent controller. However, for the scheme of Fig. 6.8, there are \( n \) sets of mixing blocks to find the global control signals with respect to wind speed changes at any local fault interval. Here, another mixing block would combine the resultant \( n \) control signals in order to generate the final control command that should be sent to the actuator.

6.2.4. Simulation Verification

The wind and fault profiles are the same as the ones used in the previous simulations for the FTC design in Fig. 5.7. Generator speed and rotor speed for the proposed wind-dependent active FTC are compared with those of the active FTC in Chapter 5, and the results are shown in Fig. 6.11. It can be seen that ignoring the complexity of the design, the wind-dependent idea outperforms the previous design in generator speed regulation. The same must be true for rotor speed regulation since, ideally, they differ only by a gearbox ratio. This is shown in Fig. 6.11.

Fig. 6.11: Comparison of wind-dependent active FTC (dashed red) and active FTC (solid blue). Fault parameter, generator speed (rpm) and rotor speed (rpm) are shown from top to bottom.
The pitch actuation signals are also presented in Fig. 6.12 where it can be seen that the wind-dependent FTC design has slightly more demand than the active FTC. However, it should be noted that the better regulation performance of the wind-dependent approach is because of the accurate pitch angle signal which is due to having different controllers for wind speed axis in Fig. 6.8. Basically, this shows that incorporating the wind-dependent uncertainty in the design of the global controller will help achieve a better closed-loop performance. However, the difficulties in design and implementation due to having many local controllers would be a weak point comparing to the active FTC. Further cost analysis should be performed in order to check the feasibility of this idea for WT applications.

Fig. 6.12: Comparison of wind-dependent active FTC (dashed red) and active FTC (solid blue). Pitch angle, pitch rate (deg./s) and pitch acceleration (deg./s²) are presented from top to bottom.
CHAPTER 7
DESIGN SUMMARY AND FUTURE WORK

This chapter provides some discussions on the proposed idea for WT application and lists possible future work to improve the design.

7.1. Design Summary

New controllers are proposed in this thesis that show the feasibility of active robust control applied to WT control. Various control objectives are defined that are intended to be addressed through the proposed controllers. The tradeoffs in control objectives are done in the frequency domain through the use of well-known robust control theory. Two types of uncertainties have been considered in modeling: (a) unstructured dynamics uncertainty for unmodeled dynamics, and (b) structured parametric uncertainties for fault and wind indices. This results in a robust performance problem that should be solved using a suitable algorithm such as the mixed μ approach.

Three controllers are designed here that try to address different combinations of parametric uncertainties with dynamics uncertainty: (a) FTC, (b) wind-dependent controller, and (c) combined FTC and wind-dependent controller.

For FTC, fault in the pitch actuator is actively compensated by the local controllers. These local controllers are robust against the changes in the fault parameter.

Wind-dependent controller addresses the wind-dependent behavior of WT model by mixing the local controllers that are robust with respect to the changes in wind parameter.

Finally a 2-dimentional design is proposed in order to handle both fault and wind-dependent behavior of the WT linear model.

All these designs are passively robust with respect to unmodeled dynamics uncertainty of WT. In addition, the robust control concept makes it possible to indirectly address the wind disturbance rejection property as a design performance criterion. The simulation results verified the effectiveness of the ideas put forth here in terms of generator speed regulation and the required control efforts. However, further verification is needed before these ideas can be implemented in practice.

7.2. Practical Considerations for Field Test on CART3

The main issues that need to be considered are listed as follows:
1. In design of local controllers, it is assumed that the changes in parametric uncertainty (i.e., fault parameter and wind parameter) are very smooth. In reality, this is true for the fault parameter; however, it is still necessary to filter out the high frequency components of the wind speed before mixing the local controllers. Although the wind-dependent behavior of the WT model depends on the mean wind speed (and not the turbulent component), passing the high frequency signal to the mixing block may lead to instability of the closed-loop system.

2. The design is limited to the pitch control of WT in region 3. However, during field tests, it is likely that the wind speed profile instantaneously passes to region 2 where the generator torque controller is the main controller in the loop. This may result in an unstable closed-loop system as shown in Fig. 7.1.

Fig. 7.1: A bad transition between regions 2 and 3. The top plot is a hub height wind speed that goes back and forth between the two regions. The other two plots represent the corresponding rotor and generator speed signals with the active robust FTC in the loop.

3. The errors considered in this research cover the effects of using LIDAR averaged measurement or estimation of wind speed for a turbulent wind profile with vertical and
horizontal shear. However, in real situations, this error will be magnified due to the wind evolution in front of the turbine. This has not been considered here.

4. It is assumed here that the fault estimator correctly detects, isolates and estimates the fault. The isolation is usually not problematic because there is only one fault in the system. Also, the detection and estimation do not change the overall performance of the closed-loop system due to the controller’s robust multiple model nature. However, this may raise the need to modify the design of local controllers which may end up being different from the proposed controller set presented in Chapter 5.

7.3. Future Work

Some possible ideas to improve the current research are listed below:

1. The robust control design can be achieved by using suitable linear matrix inequality techniques in order to relax the assumption on the rate of changes in scheduling parameters.

2. The design can be enhanced with a transition algorithm between the regions to avoid possible instability. The result of such an algorithm with anti-windup modification is given in Fig. 7.2 for a typical high turbulent wind profile that covers regions 2, 3 and 2½ having the fault scenario as in Fig. 7.1. However, this issue was not considered in the current work.

3. As discussed in Section 6.1.4, the proposed controller may worsen some of the mechanical loads of the system when compared to the baseline controller for CART3. Although the improvement level achieved is acceptable as is, the results can be further improved by designing a new controller with notch filter behavior in the frequency domain. A very simple design that only addresses the loads on CART3 is proposed in [105] that can be used here to identify the right tradeoff for load reduction in addition to the previous objectives.

4. Design of a fault estimation block can be another future plan. This can be achieved through a recursive least design or robust adaptive estimation techniques for parametric modeling of the actuator. The result of a Lyapunov design method with parameter projection modification is depicted in Fig. 7.3. However, possible improvements in estimation precision are left as an open issue, and are not discussed here.
An anti-windup transition algorithm is developed for active FTC design for a wind profile with mean of 14.5 m/s and turbulent intensity of 17% with a fault scenario as Fig. 7.1. The anti-windup strategy prevents instability and keeps the pitch actuation within acceptable limits. It should be noted that when the wind speed passes to region 2, the generator and rotor speeds drop since the wind does not have enough power to turn the turbine at its rated speed.
Fig. 7.3: Robust adaptive fault parameter estimation for a second order parametric model of the pitch actuator with noisy measurement.
REFERENCES


[69] Pisu P., Ayalew B., "Robust Fault Diagnosis for a Horizontal Axis Wind Turbine", *18th IFAC World Congress Milano*, pp. 12372-12379, Italy, 2011.


