Model-free control design for permanent magnet synchronous generator in wind energy conversion systems

by

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Declaration

I, Zholtayev Darkhan Muratovich, declare that the research contained in this thesis, unless otherwise formally indicated within the text, is the author's original work. The thesis has not been previously submitted to this or any other university for a degree and does not incorporate any material already submitted for a degree.

Signature:

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Abstract

This research, conducted as part of a PhD program at Nazarbayev University, investigates advanced control methods for electric engines, with a focus on *Wind Energy Conversion Systems* (WECS), in pursuit of sustainable and efficient energy solutions. Electric machines permeate many facets of our daily lives, ranging from household appliances to industrial applications, making their efficient management a necessity. WECS, which are characterized by inherent nonlinearity, present challenges that necessitate sophisticated control strategies for efficient power harvesting, assuring power quality, and minimizing system wear and tear.

The investigation of an advanced model-based control method, *Super-Twisting Adaptive Sliding Mode Control* (ST-ASMC), for *Permanent Magnet Synchronous Generator* (PMSG)-based WECS is the focus of this research. ST-ASMC is presented as an effective solution, preserving the robustness characteristics of conventional sliding mode control while reducing chattering via gain adaptation and the generation of second order sliding modes. ST-ASMC facilitates optimal power acquisition by resolving a nonlinear multi-input multi-output tracking control issue. The proposed control method outperforms other sliding mode control techniques in the presence of variations in stator resistance, stator inductance, and magnetic flux linkage, as determined by comparative simulation studies employing actual wind speed data.

In addition, this thesis introduces a novel context for implementing a model-free control method based on the *Twin Delayed Deep Deterministic Gradient Descent* (TD3) technique within the context of PMSG-based WECS. This method is effective for adapting to dynamic uncertainties and disturbances in the WECS. TD3 is effective, stable, and robust, leveraging deep neural networks and reinforcement learning to incrementally improve decision-making. Notably, this model-free control method requires minimal understanding of the wind power conversion system, relying only on wind speed, turbine diameter, tip-speed ratio, electromagnetic torque, and stator direct current. In other words, for the first time in the context of WECS *deep reinforcement learning* (DRL) was implemented as the sole controller for the machine side. Through exhaustive evaluations, the TD3-based *Maximum Power Point Tracking* (MPPT) algorithm demonstrates adaptability and efficiency under varying conditions and system parameter fluctuations, validating its potential to enhance the performance of WECS for sustainable development and, in certain metrics, outperforming the *Linear Quadratic Regulator* (LQR) model.

In conclusion, this thesis advances the field of control methods for electric drives in WECS by proposing and validating advanced control strategies that can considerably contribute to the efficiency and sustainability of wind energy harvesting and conversion systems.

Acknowledgments

I commence by expressing my sincere appreciation to my respected professor, Ton Duc Do. He was the person who introduced me to the complex academic universe and the intriguing field of robotics. Not only was he a distinguished guide, but he was also a loyal friend who supported me during difficult times. His firm confidence in me instilled fortitude to maintain my motivation and self-confidence even during difficult times. Throughout my PhD research, he gave me the freedom to investigate unknown territory while providing me with insightful direction.

I was overwhelmed by financial constraints and familial responsibilities as a result of my doctoral studies. Nonetheless, this trial honed my agility, bolstered my confidence, and enhanced my versatility across numerous disciplines.

I was privileged to work with an expert like Matteo Rubagotti, whose guidance was crucial to my contributions to high-impact-factor journal articles. I was able to publish in prestigious journals as a result of his illuminating insights and invaluable feedback.

Professor Husein Atakan Varol, whose infectious enthusiasm for robotics and deep learning algorithms ignited my own, has my deepest gratitude. He taught me invaluable lessons about the art of research, staying apprised of emerging trends, and acquiring broad knowledge ranging from technical journal articles to nonfiction books.

Professor Berdakh Abibulayev, who gave me the opportunity to engage in the exciting field of deep learning and gave me my first hands-on experience, has my sincere appreciation.

My deepest gratitude goes to my wife, Nurziya, whose unwavering support has been indispensable throughout my PhD voyage. Her forbearance and understanding gave me the space to work diligently while also providing me with much-needed strength during difficult times, especially as our family grew.

A special note of appreciation to my children, Zhahanger and Tomiris. Their presence made my PhD journey both challenging and exciting. I hope that when they are older and read these acknowledgements, they will be proud of their father's achievements.

My heart is filled with gratitude for my parents, who gave me the opportunity to pursue a PhD and provided unwavering support during difficult times. To my sibling, who encouraged me to pursue a PhD because he saw my potential as a successful researcher, I offer my sincerest gratitude.

Lastly, I would like to thank my coworkers and friends: Kanat, Bayandy, Tolegen, and all the unnamed individuals who have impacted my voyage. Each has added a distinct colour to the palette of my success and made my PhD journey significantly more pleasurable and memorable.

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Preface

The motivation for my research was derived from a longstanding interest in pioneering individuals such as Elon Musk, who disrupted the conventional automotive sector and brought attention to ecological preservation. The rapid growth of artificial intelligence, specifically the advent of deep learning algorithms, has heightened my curiosity. The concept of intelligent systems, which possess the ability to imitate the cognitive functions of the human brain, including learning, adaptation, and decision-making, has captured my attention. Under the guidance of my valued supervisor, I began my exploration of the fascinating realm of model-free control techniques for electric drives.

The developmental path of this thesis can be likened to ascending a hill, with the ultimate goal of reaching the top, which is perceived as a mountain. During the preliminary phases, our emphasis was on acquiring a comprehensive knowledge of model-based control techniques prior to delving into the more intricate domains of data-driven, model-free controls. The process of transition was perceived as a formidable task, akin to taking a leap of faith into an unfamiliar and uncertain realm. At the start, my expertise in the area of deep reinforcement learning was limited, and the application of this technique for electric drives posed a significant challenge. However, with the advancement of Artificial Intelligence and significant enhancements in computational tools like MATLAB and Python frameworks, the landscape of control systems, specifically in the domain of power electronics and electric drives, has transformed dramatically. These developments have facilitated the implementation of *Deep Reinforcement Learning* (DRL) as a stand-alone controller, specifically as a *Maximum Power Point Tracking* (MPPT) controller.

This task, which appeared exceedingly challenging just half a decade ago, is now well within our grasp. It's astounding to see how these technological advancements have effectively bridged the gap, enabling us to accomplish what was once considered a daunting task. Truly, the interplay of AI development and the evolution of computational tools is paving the way for revolutionary changes in the field of power electronics and electric drives, serving as a testament to the adage "Nothing is impossible".

In retrospect, the experience evokes a sense of surrealism. The elevation that I formerly aspired to be a mountain presently serves as evidence of my achievements, notwithstanding their perceived insignificance during their inception. I engaged in a process of active participation, acquisition of knowledge, and achievement of success. Ultimately, the expedition encompassed more than the attainment of a doctoral degree

or the satisfaction of scholarly responsibilities. The experience encompassed the acquisition of knowledge, the surmounting of obstacles, and the elation of witnessing the manifestation of a long-held aspiration.

It is imperative to acknowledge the indispensable input of my co-supervisor, whose proficiency substantially augmented the calibre and influence of our research. The aforementioned expedition was not an individual undertaking but rather a cooperative pursuit, a splendid harmony of communal concepts, unwavering exertion, and persistent resolve. The preface serves as a modest expression of gratitude to all individuals who contributed to the development of this academic pursuit and dissertation.

This thesis marks the commencement of a journey towards scaling unexplored heights, undertaking uncharted endeavours, and expressing gratitude to unacknowledged entities.

Zholtayev Darkhan Muratovich
Astana, August 2024

Chapter 1

Introduction

1.1 Background

1.1.1 History of wind power conversion systems and it is evolution

The field of *wind energy conversion systems* (WECS) has experienced notable progressions in terms of design, materials, and control methodologies subsequent to the initial development of the wind turbine by Charles F. Brush in 1888 [1]. In the experimental development of the *diffuser-augmented wind turbine* (DAWT), the early stages involved the utilization of diverse screen meshes to replicate the energy extraction mechanisms of a wind turbine, as reported by Gilbert et al. in 1983 [2].

Figure 1.1: Diffuser-augmented wind turbine (DAWT)

Figure 1.2: Old windmill

Over the course of the last two millennia, the implementation and utilization of wind turbines have been primarily shaped by fortuitous support from enthusiasts, rather than formal aid from authoritative entities. In the aftermath of World War Two, there was a notable upswing in the exploration of wind energy as a potential solution to fuel shortages, escalating electricity demand, and economic and political challenges that

prompted countries to increasingly depend on their own indigenous energy resources. The individual's inclination towards this subject matter was partially motivated by the notion that the reserves of fossil fuels were finite and the increasing comprehension of aerodynamic principles. Due to the finite nature of fossil fuel resources, many progressive nations have prioritized research into the extraction of ambient energy since 1973, citing economic and safety concerns among other factors. Wind turbines have been implemented on a global scale by enthusiasts, surpassing the level of official support [3].

According to Serrano (2016) [4], there has been a substantial increase in the dimensions of wind turbines over the years. Specifically, the rotor diameter, hub height, and rated power have increased from 30 m, 30 m, and 300 kW, respectively, in the late 1980s to 92.7 m, 87.7 m, and 2.1 MW in 2016. The process of converting wind kinetic energy into mechanical energy is accomplished by WECS through the utilization of rotor blades, which are subsequently converted into electrical energy by means of a generator, as noted by Wu et al. (2011) [5]. The remarkable expansion of the wind energy sector can be ascribed to apprehensions regarding ecological matters, as well as the exploration and advancement of pioneering expense-reducing technologies [6]. The wind energy sector has witnessed the emergence of novel wind energy conversion systems, including the cross-flow type vertical wind power generation system, as reported by Chung et al. (2011) [7]. The dependable and effective transformation of wind energy through wind turbines is contingent upon both the dependability of the wind power generation equipment and the wind turbine control system [8]. According to Meera et al. (2015) [9], there has been a rapid increase in the global wind energy capacity, making it the fastest-developing renewable energy technology.

1.1.2 Control aspects of the wind turbine and its importance

The implementation of control schemes in WECS is aimed at achieving optimal operation, enhancing the efficiency of wind energy conversion, minimizing energy costs, prolonging the lifespan of wind turbine components, mitigating structural loading, reducing turbine downtime, and ensuring superior dynamic and steady-state performance. The significance of wind turbine control is contingent upon the particular type of turbine employed.

The Type 1 configuration of WECS employs a *squirrel cage induction generator* (SCIG) with a fixed speed tolerance of ±1%. The control system for this configuration is straightforward and primarily concerned with ensuring consistent power output and speed. The Type 2 WECS employs a semi-variable speed (±10%) *wound rotor induction generator* (WRIG), wherein the control system is required to regulate the rotor resistance to enable variable speed operation. The Type 3 WECS configuration, which utilizes a semi-variable speed (±30%) *Doubly Fed Induction Generator* (DFIG), requires the

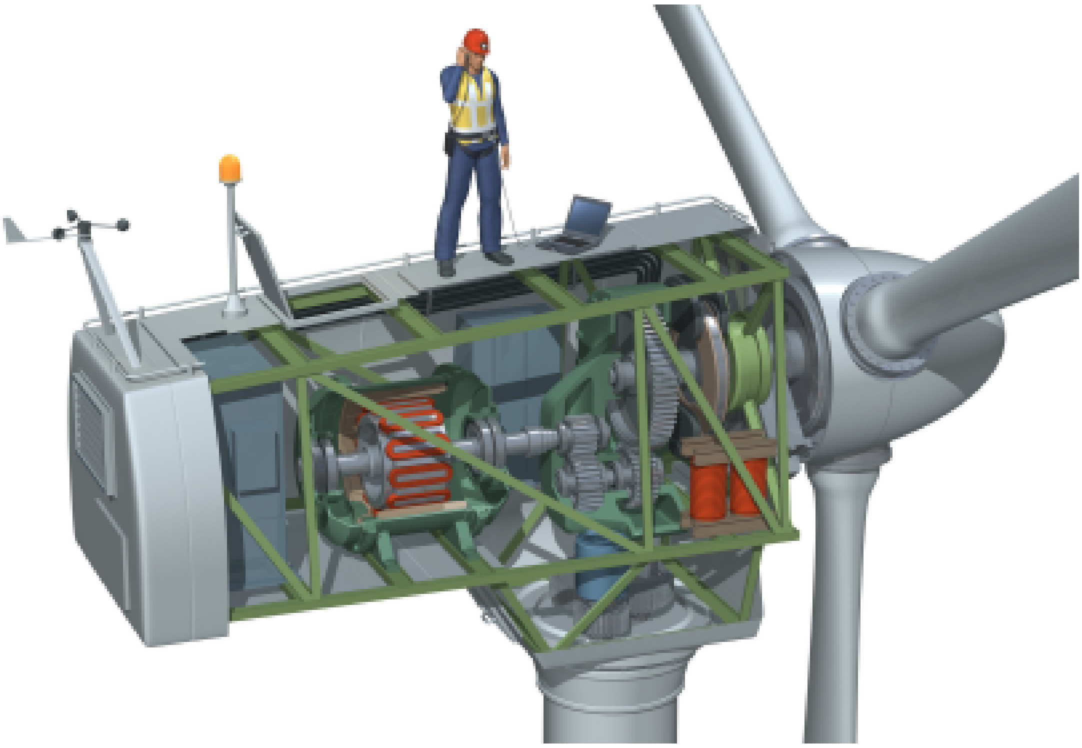

Figure 1.3: Controlling a wind energy conversion system (WECS)

control system to regulate both stator and rotor currents in order to facilitate variable speed operation. The Type 4 WECS employs a full-variable speed (0-100%) SCIG, *Permanent Magnet Synchronous Generator* (PMSG), or *Wound Rotor Synchronous Generator* (WRSG). In this configuration, the control system must regulate both the generator torque and pitch angle to enable variable speed operation.

The aforementioned progression in the development of wind power conversion systems, transitioning from fixed-speed to variable-speed wind turbines, indicates a clear requirement for an increased number of power converters and electrical components to facilitate the control of each constituent element upon implementation. The efficacy of power harnessing and subsequent conversion into electricity is contingent upon the effectiveness of control methodologies. Typically, the controller is responsible for overseeing multiple variables, including but not limited to wind speed velocity, wind direction, generator voltages and currents, filter or direct current link or (DC)-link voltages (if applicable), and grid voltages and currents. The controller then proceeds to regulate the system's operating states or variables to align with the reference value or remain within the established boundaries. As per Yaramasu et al. (2015) [10], the control variables for generator speed, torque, or power in various schemes are typically determined by a *Maximum Power Point Tracking* (MPPT) algorithm.

1.2 Motivation

1.2.1 Need for an Effective Control Method in Wind Energy Conversion Systems

The optimization of wind turbine performance, taking into account both mechanical and electrical aspects, necessitates the implementation of effective control methods [11]. The conversion of mechanical energy to electrical energy in large wind turbines is a multi-stage process that entails transferring the energy to the DC-link and ultimately integrating it into the grid. According to Yaramasu et al. (2015) [10], control strategies are implemented at every stage to reduce electrical losses, improve power conversion efficiency, and guarantee seamless synchronization with the electric grid network.

Notwithstanding their efficacy in certain scenarios, model-based control techniques may prove insufficient in the context of electrical systems that exhibit continuous operation and experience time-varying parameters due to thermal effects, thereby leading to model mismatch and parameter variation. The system's performance can be adversely affected by various factors such as increased resistance in the generator's winding, deteriorating magnetic inductance, rising inertia, unmodeled nonlinearities, and external disturbances caused by wind gusts. This has been highlighted in previous studies [12, 13, 14].

Over the course of several decades, scholars have endeavoured to devise adaptive control techniques that account for both mechanical and electrical factors, in order to tackle the aforementioned obstacles. Notwithstanding, the aforementioned techniques are typically characterized by high computational costs and intricate control designs, rendering them suboptimal for practical implementations [15, 16, 17].

1.2.2 Motivation for the model-free control method in wind energy conversion systems

The process of acquiring a precise and resilient model of an intricate system presents considerable challenges, encompassing several technological and computational obstacles. Although various techniques have been devised to enhance system robustness, the effectiveness of advanced observers and control mechanisms is generally constrained by notable limits. For example, several modified observers, such as the disturbance observer (DOB) and the extended state observer (ESO), have been developed with the purpose of forecasting and monitoring disturbances and discrepancies in parameters. Nevertheless, the efficacy of these strategies is heavily reliant on the specific physical parameters and structural characteristics of the system under consideration, hence imposing certain limitations [18].

In order to overcome these constraints, researchers have proposed the utilization of model-free Model Predictive Control (MPC) techniques, which seek to substitute pre-existing models with data-derived alternatives. The model-free approaches rely exclusively on the input and output data that is measured, with the aim of mitigating the impact of any physical characteristics. Although there are certain benefits associated with these, they also provide their own unique set of difficulties, notably the need for precise and dependable data [19].

Furthermore, the utilization of common approximations in order to streamline system descriptions presents other complexities. An instance where the assumption of linear magnetic flux-current characteristics or constant stator resistance may lead to parameter mismatches, hence impacting the accuracy of the model. While the utilization of observers can partially alleviate these discrepancies, they are accompanied by their own array of challenges, encompassing concerns pertaining to convergence, stability, and precision. The use of online parameter tracking, while beneficial for improving model-based techniques, necessitates increased computational resources and meticulous tweaking endeavours.

Essentially, any technique designed to enhance the accuracy and resilience of a model is accompanied by its own distinct set of compromises and limitations. Regardless of whether an individual chooses observer-based methods or model-free alternatives, there are ongoing obstacles to attaining a completely accurate and resilient model. Therefore, the pursuit of accurate system modelling continues to be a persistent undertaking, requiring continual research and optimization.

One benefit of using a model-free control approach is that it reduces the effect of physical parameters while also making the system more stable. Traditional model-based control works best when the physical parameters of the plant are accurate, which can be hard to do because they change all the time while the plant is running. By way of comparison, a model-free methodology substitutes the previously established model of the plant with a data-oriented model that lacks any physical parameters. This implies that the model information is inherent in it, owing to its reliance on the measured input and output data. Hence, it can be argued that a model-free methodology could offer benefits over conventional model predictive control in scenarios where the determination of physical parameters poses a challenge [18].

To keep the motivation part compact, in subsection 1.5.3.5, in table 1.1, a summary of the literature review is given in a more convenient table form. There, readers can find research works done before this work and make clear what gaps this work fills that were not considered in previous works. Which clearly points out challenges and unsolved issues that have WECS.

1.3 Objective

The main aim of this doctoral dissertation is to create an innovative control design that does not rely on a specific model for PMSGs in WECS. The proposed design should guarantee reliable and effective performance in the presence of different operating conditions, such as disturbances, uncertainties, and variations in parameters. The suggested approach for control will be subject to thorough scrutiny, simulation, and verification via comprehensive experimental investigations, with the ultimate objective of augmenting the overall effectiveness, dependability, and efficacy of WECS based on PMSG. Several model-free control techniques have been applied and developed in wind energy conversion systems and electric motors. Intelligent control techniques, such as *artificial neural networks* (ANNs) and control methods based on fuzzy logic, are illustrative examples. The utilization of various control methods, such as *model reference adaptive control* (MRAC), is often employed in tandem with other control techniques. MRAC necessitates a nominal model of the system, as noted by Bose et al. (2020) [20] in their research on power control. In the context of electric motor systems or WECS, reinforcement learning serves as a model-free control technique that supplants the existing control loop. However, it is important to note that a separate PI control is still required for the speed loop [21, 22] and in mentioned works. This study aims to devise a control approach that is independent of system parameters and possesses resilience against model uncertainties, disturbances, and parameter fluctuations. This approach is intended to be model-free and create a control method that can function independently without the need for additional supplementary control methods as in mentioned existing works.

1.4 Wind energy conversion systems

1.4.1 Generator rotor axis direction based types of wind turbines

The evolution of wind turbines has been marked by substantial progress in their design, manufacturing, and operational aspects. The two primary classifications of wind turbines are *horizontal axis wind turbines* (HAWT) and *vertical axis wind turbines* (VAWT), which are differentiated based on their respective axes of rotation. HAWTs are widely utilized in comparison to VAWTs, which are less prevalent but offer distinct benefits in specific contexts. VAWTs are commonly utilized in residential settings due to their high efficiency and suitability for low-volume production.

The VAWT possesses a rotational axis that is oriented at a right angle to the Earth's surface, thereby enabling it to harness wind energy from all directions for the purpose of electricity generation. In contrast, HAWT are frequently employed for generating significant quantities of energy, necessitating substantial capital investment and a

Figure 1.4: Horizontal-axis wind tur
bine

Figure 1.5: Vertical-axis wind turbine

larger installation area in comparison to VAWT. The HAWT is oriented parallel to the prevailing wind direction to facilitate the conversion of wind energy into electrical power. According to Mohamad et al (2015) [23] and Kassem et al. (2019) [24], the installation of wind turbines necessitates a substantial tower and blade, as well as the expertise of proficient labourers.

1.4.2 Location-based Wind Turbine Configurations

There are notable distinctions between on-shore and off-shore wind turbines, encom passing factors such as power generation capacity and physical dimensions. Regarding power generation, both onshore and offshore wind turbines utilize the kinetic energy of the wind to produce electrical energy. Nevertheless, disparities exist in their respective capacities for power generation. In general, offshore wind turbines exhibit a greater capacity for power generation when compared to their onshore counterparts. The reason for this phenomenon is that offshore wind resources generally exhibit greater strength and consistency compared to onshore wind resources (Lignarolo, 2014) [25]. In addition to their capacity for accommodating larger and more powerful turbines, offshore wind farms possess the advantage of heightened electricity generation potential. An illustration of this can be seen in the Haliade-X wind turbine, which possesses a power capacity of 12 MW and a rotor diameter measuring 220 m (Cao et al., 2020) [26]. However, the size and power generation capacity of on-shore wind turbines is constrained by factors such as land availability and height restrictions (Hongisto, 2017) [27].

In relation to dimensions, offshore wind turbines typically exhibit greater magnitude compared to their onshore counterparts. According to Hongisto (2017) [27], the hub height of contemporary on-shore turbines with a capacity of 5 MW is commonly 125 m or higher. In contrast, the hub height of on-shore turbines with a capacity of 300 kW in 1995 was approximately 30 m. According to Cao et al. (2020) [26], offshore

wind turbines have the potential to be significantly larger, with rotor diameters reaching approximately 220 m. The increased dimensions of offshore turbines facilitate enhanced power generation capabilities, as they enable the capture of a greater amount of wind energy. Nevertheless, the increased dimensions of these structures also give rise to various maintenance and repair difficulties, particularly for offshore wind farms situated at considerable distances from the coastline (Cao et al., 2020) [26].

An additional factor to take into account is the ecological implications. According to Da et al. (2022) [28], offshore wind turbines exert a more pronounced environmental influence on the seabed in comparison to onshore turbines. The installation of offshore turbines necessitates the establishment of stationary positions, a process that can potentially disrupt marine ecosystems and habitats. Conversely, land-based wind turbines possess a reduced environmental impact due to their installation on terrestrial surfaces.

In summary, there exist notable distinctions between on-shore and offshore wind turbines with regard to their capacity for power generation, physical dimensions, and environmental implications. In comparison to on-shore turbines, off-shore turbines typically possess greater power generation potential and exhibit larger physical dimensions. Nevertheless, the maintenance and repair of offshore turbines are accompanied by challenges due to their larger size. Moreover, offshore turbines exhibit a greater environmental impact on the seabed. Conversely, land-based turbines exhibit a reduced ecological impact, albeit with constraints in terms of their dimensions and capacity for power generation.

1.4.3 Power Electronics in Wind Turbines: The Evolution from Fixed to Advanced Variable Speed Configurations

Over the course of the last thirty years, WECS has undergone significant development, resulting in a range of configurations that aim to maximize energy conversion efficiency and extend the operational lifespan of wind turbines. The principal electrical constituents in WECS are the generator and power electronic converter. There exist five predominant configurations that have been extensively documented and commercialized.

1. Type 1: Fixed-speed (±1%) WECS with SCIG
2. Type 2: Semi-variable speed (±10%) WECS with WRIG
3. Type 3: Semi-variable speed (±30%) WECS with DFIG
4. Type 4: Full-variable speed (0-100%) WECS with SCIG, PMSG, or

WRSG 8

Wind energy conversion systems

Figure

1.6: Onshore wind turbine Figure 1.7: Offshore wind turbine

The implementation of variable-speed operation in wind turbines has been shown to improve energy conversion efficiency, mitigate mechanical stress caused by wind gusts, decrease the likelihood of wear and tear on gearboxes and bearings, reduce maintenance demands, and extend the overall lifespan of the system. The utilization of power electronic converters for regulating the generator speed is instrumental in enabling variable speed operation in Type 2, Type 3, and Type 4 configurations of WECS.

The utilization of variable-speed wind turbines presents a notable advantage over fixed-speed wind turbines due to their ability to proportionally adjust the rotor speed in response to low to moderate wind speeds. The aforementioned practice enables them to sustain an ideal tip-speed ratio, thereby optimizing their aerodynamic efficacy. At the point of maximum aerodynamic efficiency, there is also a corresponding maximum in energy conversion. In comparison, wind turbines with fixed speeds operate at a steady rotor speed, independent of the wind speed. This results in suboptimal aerodynamic efficiency and energy conversion for varying wind conditions, as noted by Sun et al. (2005) [29] in their study on flicker.

Utilizing a variable-speed wind turbine control strategy in a small-scale wind farm offers advantages such as compliance with the latest wind farm grid code and resolution of the issue of fixed-speed wind generators' significant reliance on reactive power. This objective is accomplished through the incorporation of *Flexible AC Transmission*

Systems (FACTS) (A power transmission system is a collection of stationary equipment designed for the purpose of transmitting electrical energy in the form of alternating current (AC). The purpose of this technology is to improve the controllability and enhance the power transfer capability of the network. The system typically operates on power electronics principles.) devices, which may result in an augmented overall expenditure. In this regard, some authors introduced a novel approach to managing a small wind farm that effectively tackles the aforementioned concerns [30].

The application of control theory is of utmost importance in contemporary wind turbines and wind farms. The primary objective of the WECS is to attain optimal operational efficiency while minimizing energy costs, enhancing the durability of wind turbine components, mitigating structural loading, minimizing downtime, and delivering superior dynamic and steady-state performance. The intricacy of control systems is contingent upon the wind turbine type utilized, necessitating distinct modifications to attain the most favourable variable speed operation for each configuration.

In general, controllers are responsible for overseeing a range of parameters, including but not limited to wind speed and direction, generator voltages and currents, grid voltages and currents, as well as filter or dc-link voltages. The operators modify the operational states or variables of a system in order to sustain reference values or establish boundaries. The MPPT algorithm is typically responsible for providing reference control variables, such as generator speed, torque, or power, as indicated by previous studies [10, 31].

1.4.4 Different generator types in wind energy conversion system

WECSs employ diverse generator technologies to transform wind energy into electrical energy. The PMSG, DFIG, and fixed-speed asynchronous generators are the prevailing generator types utilized in WECS.

PMSG and DFIG are commonly employed in wind turbine generators that operate at varying speeds. The PMSG is a type of generator that operates without a gearbox, thereby mitigating the need for maintenance and enhancing overall efficiency. Furthermore, the aforementioned technology exhibits a notable power density and reduced mass, rendering it a viable option for employment in offshore wind turbines. The DFIG is an electro-mechanical device that utilizes gearing to increase power conversion in wind technology, thereby facilitating the requirements of the generator. The cost of this technology is comparatively lower than that of PMSG, and it has the ability to function at varying speeds [32, 33, 34, 35]

The axial flux synchronous generator is a contemporary model of generator that has been devised for the purpose of conversion. The axial flux generator model exhibits several benefits in comparison to alternative models, such as superior power density,

reduced weight, and heightened efficiency, as evidenced by studies conducted by Akiki et al. (2018) and Chan et al. (2007) [36, 37].

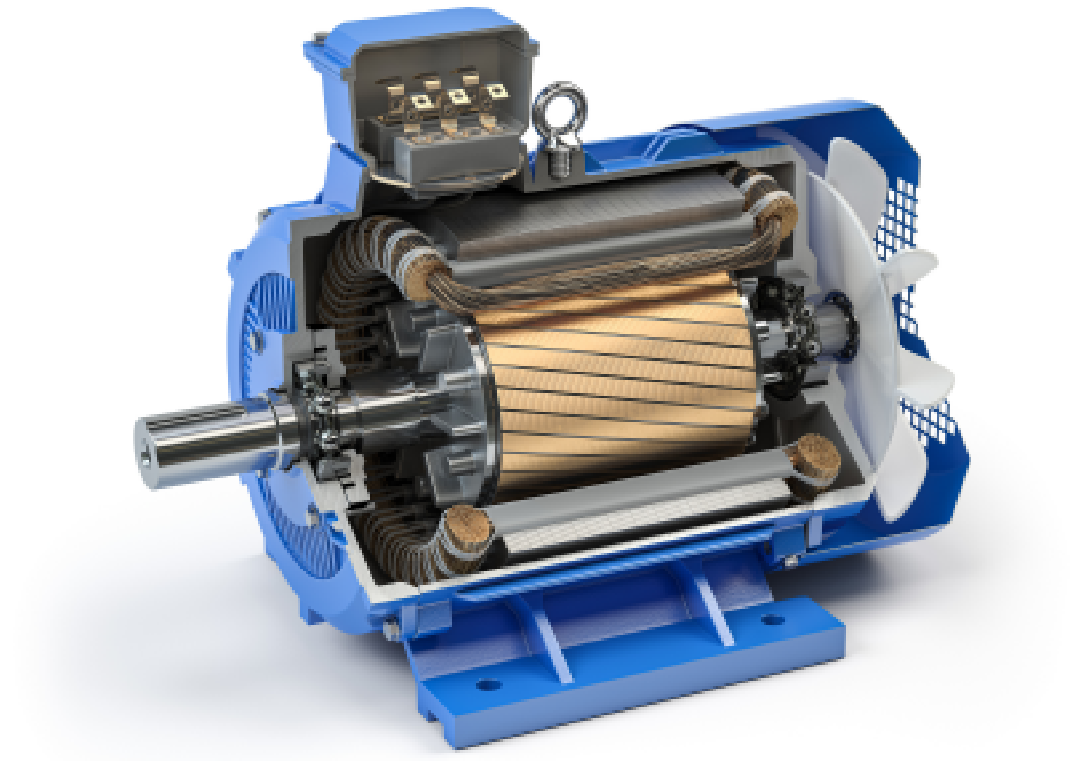

Figure 1.8: Generator

The implementation of DFIGs was initiated during the latter part of the 1990s with the aim of fulfilling the need to minimize the noise level and mechanical strain on the drivetrain, enhance the power quality, and augment the level of captured power. The operational mechanism of a DFIG bears a resemblance to that of a SCIG. However, unlike the SCIG, the rotor of a DFIG is equipped with a three-phase winding instead of a squirrel-cage rotor. The direction of active power flow can be regulated to attain variable speed operation, while the rotor current in the converter can be utilized to regulate the reactive power. According to Goudarzi's review (2012) [38], DFIGs that utilize brushes and multiple-stage gearboxes necessitate frequent maintenance and are more susceptible to machine failure compared to PMSG-based systems.

Ultimately, the selection of generator type is contingent upon a multitude of factors, including but not limited to efficiency, maintenance expenses, and power conversion requirements. PMSG and DFIG are widely utilized generator types in WECS. However, contemporary models, such as axial flux synchronous generators, are currently under development to enhance efficiency and minimize maintenance expenses.

1.4.5 Summary of the section: Wind Energy Conversion Systems

To summarize, wind turbines have undergone notable progress in their design, production, and functionality, and can be classified into two primary categories based on their axis of rotation: HAWTs and VAWTs. The selection of the site for WECS is a critical factor, given that both onshore and offshore installations possess their respective merits and demerits. The power electronics utilized in wind turbines have undergone a transformation from static to sophisticated variable-speed configurations, resulting in enhanced energy conversion efficiency and decreased mechanical strain. Various types of generators, including PMSG, DFIG, and fixed-speed asynchronous generators, are employed in wind energy conversion systems. The selection of a particular generator type is influenced by several factors, such as efficiency, maintenance expenses, and power conversion requirements. The application of control theory is of paramount importance in contemporary wind turbines and wind farms, as it guarantees optimal functionality and maximizes the efficiency of wind energy conversion. The ongoing advancement of wind energy has led to the exploration of novel generator models, such as axial flux synchronous generators, in order to enhance efficiency and decrease maintenance expenses. The PMSG is widely utilized in the wind turbine sector due to its high efficiency, substantial torque, and minimal maintenance requirements.

1.5 Control methods in power electronics and electric drives

The following section presents a comprehensive analysis of the control techniques that are frequently utilized in power electronics and electric drives. The discussion places specific emphasis on those methods that are relevant to WECS based on PMSGs. The discourse will encompass diverse control methodologies, comprising classical, model-based, and model-free techniques, along with their corresponding merits and demerits.

1.5.1 Literature Review: Classical Control Methods in Wind Energy Conversion Systems

This subsection presents a comprehensive literature review of the prevalent model-based and model-free control methods utilized in electric drives, including electric motors and generators. The present discourse pertains to the benefits and inherent constraints associated with model-based control techniques.

1.5.1.1 *Proportional-Integral-Derivative* (PID) control in WECS

The utilization of classical control techniques, specifically *proportional-integral derivative* (PID) controllers, has been extensively applied in the fields of power electronics and electric drives. This is attributed to their uncomplicated nature, straightforward implementation, and resilience. PID controllers have been employed in PMSG-based WECS to regulate active and reactive power, sustain the DC-link voltage, and guarantee conformity with the grid.

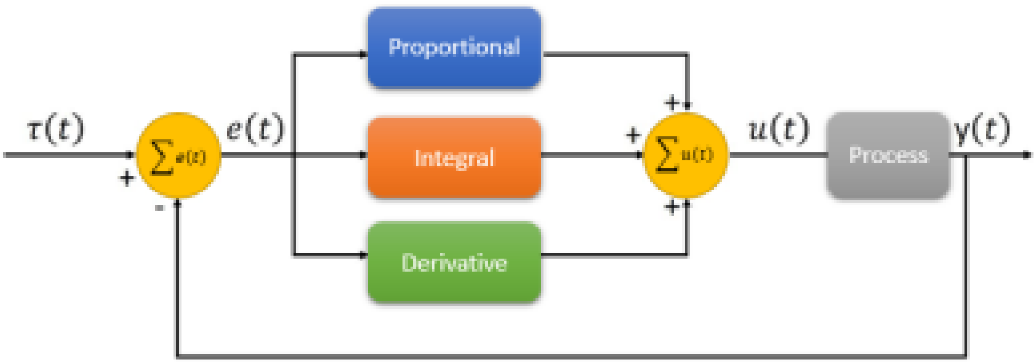

Figure 1.9: Proportional-Integral-Derivative control scheme. *τ* (*t*) - is the reference signal, *e*(*t*) - error signal, *u*(*t*) - control signal, *y*(*t*) - system output

Nevertheless, similar to other control techniques, PID control exhibits certain constraints and difficulties. One of the primary obstacles involves the adjustment of the controller to attain peak efficiency across varying operational circumstances. Inadequate calibration has the potential to result in instability, oscillatory behaviour, and suboptimal response durations. One of the challenges that must be addressed pertains to the management of nonlinearities and uncertainties within the system, as these factors have the potential to impact the precision and dependability of the controller. [39] In order to surmount the obstacles encountered, sophisticated control engineerings techniques, such as model-based control and adaptive control, can be employed in tandem with PID control to enhance its efficacy and resilience. Consequently, a plethora of adaptive PID control methods has been devised [40, 41].

1.5.1.2 *Model Predictive Control* (MPC) control in WECS

The utilization of a mathematical model of a system to anticipate its future behaviour and optimize its control inputs over a finite time horizon is known as *Model Predictive Control* (MPC). The application of MPC in WECSs has been observed for various purposes, including voltage stability control [42], optimal operation

[43], grid connection [44], power quality enhancement [45], power dispatching [46], energy storage control [47, 48], and wind power fluctuation suppression [49, 50]. Notwithstanding its benefits, MPC exhibits certain constraints when applied to WECSs. The computational complexity of the optimization problem is a primary constraint, which escalates proportionally with the system's magnitude and the prediction horizon's duration. The aforementioned circumstance may result in elevated computational expenses and delayed response durations, particularly in the context of WECSs of considerable magnitude. An additional constraint pertains to the precision of the mathematical framework employed for forecasting, which could be influenced by various uncertainties and disruptions within the system. Inaccurate or outdated models may result in suboptimal control performance and even instability, as noted by Yaramasu et al. (2015) [10]. The implementation of MPC may encounter difficulties in addressing system constraints and nonlinearities, necessitating the utilization of sophisticated methodologies such as nonlinear MPC or hybrid MPC for resolution, as noted by Garcia and Prettelt (2013) [51] and Richter et al. (2012) [52]. To summarize, MPC exhibits potential as a control strategy for WECSs due to its ability to deliver optimal and resilient control performance. Nevertheless, it is imperative to meticulously evaluate and tackle the constraints pertaining to computational complexity, model accuracy, and constraint handling in practical applications.

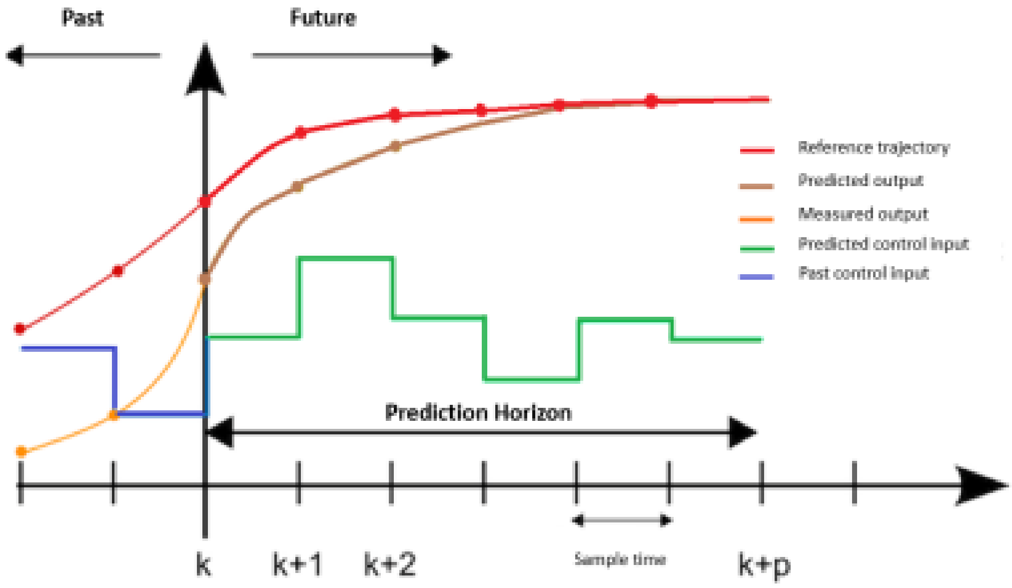

Figure 1.10: Model predictive control scheme. *k, k* + 1*, k* + 2*, .., k* + *p* - is the discrete time steps

1.5.1.3 Vector control in WECS

The management of vector control is a crucial component in the operation of WECS as it facilitates the proficient and potent regulation of the generator's active and reactive power. Various vector control techniques have been employed in WECS featuring diverse generator types, such as PMSG [53] [54], DFIG [55, 56, 57, 58], and induction generators [59]. The technique of vector control is employed to disentangle the active and reactive power components of the generator, thereby enabling autonomous regulation of these variables.

Various research studies have suggested diverse techniques for vector control in WECS. Gajewski and Pienkowski (2016) [´ 53] introduced a vector control approach for a wind turbine system that employs a direct-driven PMSG generator. Their method was demonstrated to be efficacious in simulation studies. Muhando and colleagues (2009) [60] proposed a control approach that utilizes a performability model to optimize energy conversion in low to medium wind conditions and sustain rated output in winds exceeding the rated level, while simultaneously minimizing torsional torque fluctuations. Djeriri and Ahmed (2020) proposed the implementation of vector control in control strategies for DFIG, which enables the separation of DFIG active and reactive powers and results in favourable performance in WECS. The study can be found in reference [57]. Although vector control has proven to be a viable approach for regulating the active and reactive power of generators in WECS, it is not without its constraints. A potential constraint of this approach is the necessity for precise measurement of the generator's parameters, including the rotor position and speed, which may prove difficult in certain circumstances [58]. Moreover, the implementation of vector control can be intricate and require significant computational resources, thereby augmenting the expenses and intricacy of the control mechanism.

1.5.1.4 *Linear Quadratic Regulator* (LQR), *Linear Quadratic Gaussian* (LQG) and *direct torque control* (DTC) in WECS

Various control strategies can be employed in WECSs to enhance energy conversion efficiency and mitigate adverse dynamic loads. The implementation of *Linear Quadratic Regulator* (LQR) control is a feedback control methodology that employs a quadratic cost function to optimize the control inputs. The implementation of LQR control has been utilized in wind turbines with the aim of mitigating mechanical loads on the tower and enhancing speed regulation, as reported by Narimene et al. (2022) [58].

An additional approach for control is the implementation of *Linear Quadratic Gaussian* (LQG) control. This method integrates LQR control with Kalman filtering to evaluate the system's state and enhance control efficiency. The LQG control has been implemented in the development of an optimal feedback controller for WECSs, with

the aim of maximizing energy conversion efficiency while simultaneously minimizing dynamic loads caused by wind fluctuations and ripple torque, as evidenced by the works of Rocha et al. (2009, 2011) [61, 62].

DTC has been used to handle WECS with great success. Bouhafna et al. (2019) [63] have shown that an *artificial neural network* (ANN) can be used for machine-side control in a WECS by combining it with DTC. Their study shows how well DTC and ANN work together to run a WT with a DFIG. The combination of DTC with MPPT has also been found to be a good way to get the most power out of wind blades. Bakouri et al. (2014) [64] did a study that proved this to be true. To enhance the efficiency of energy conversion and mitigate the adverse effects of dynamic loads, various control strategies such as LQR, LQG, DTC, and multi-input LQR have been implemented in wind energy conversion systems. Although LQR, LQG, and DTC have proven to be efficient control methodologies for wind energy conversion systems, they are not without their constraints. A constraint associated with LQR and LQG control pertains to their dependence on precise system models, which can pose a challenge to acquire in real-world scenarios. The presence of imprecise models can result in suboptimal control performance and potential instability, as evidenced by previous studies [62, 61]. Furthermore, the computational demands of LQG control may constrain its feasibility for real-time deployment [60].

Torque ripple stands as a prominent drawback within the context of DTC in WECS. Torque ripple is characterized by the oscillation in torque output during the operational phase, resulting in mechanical strain and heightened deterioration of the generator's constituent parts. The absence of a gearbox in direct-drive systems, wherein the generator is directly linked to the wind turbine, presents a notable challenge. The occurrence of torque ripple in DTC can be attributed to the discrete switching behaviour of the inverter, leading to the generation of non-uniform torque output. Various approaches have been suggested in the literature to mitigate torque ripple in DTC, including the application of predictive control algorithms and optimization methodologies (Sun et al., 2016) [65].

One additional drawback of DTC in WECS pertains to the intricate nature of the control algorithm. The estimation of various parameters, such as the stator flux and torque, is a necessary aspect of DTC. However, this process can pose challenges and require significant computational resources. Furthermore, the implementation of DTC frequently necessitates the adjustment of weighting factors in order to attain the most favourable control performance. The process of tuning can be a lengthy endeavour and may necessitate specialized expertise (Guo, 2017) [66]. In order to tackle this matter, researchers have put forth simplified DTC methods. These methods aim to eliminate the requirement for weighting factors and alleviate the computational load [66].

Moreover, it should be noted that the application of DTC may not be universally

applicable to all categories of wind turbines. The DTC technique is predominantly intended for application in PMSGs, which are widely utilized in small-scale wind turbines. DTC compatibility with induction generators may be hindered by their distinct operational characteristics. Hence, the utilization of DTC in WECS is constrained to specific generator types (Behjat et al., 2016) [67].

1.5.2 Adaptive Sliding Mode Control in Wind Energy Conversion Systems

The utilization of *sliding mode control* (SMC) is a prevalent and resilient control approach in WECS for the purpose of governing the power produced by wind turbines. The system's ability to manage uncertainties and disturbances can be achieved through the implementation of a sliding surface that directs the system's state trajectory towards a desired equilibrium point, as demonstrated in studies [68, 69, 70, 71]. Various research studies have suggested diverse SMC techniques for WECS, which encompass the integration of SMC with other control strategies, or the inclusion of fuzzy logic or neural networks.The following sources have been cited: Liu et al. (2019), Sarsembayev et al. (2020), Tola et al. (2022), Horch et al. [72, 73, 74, 75, 76].

The objective of the standard SMC is to guide the system state towards a properly designed sliding manifold within a finite time frame, specifically during the reaching phase. Upon entering the sliding manifold, the system initiates the sliding phase, during which the system state is constrained to remain on the manifold, and any matched disturbances are compensated with perfect precision [77]. The discontinuous control action employed by SMC results in the occurrence of high-frequency oscillation of the state around the sliding manifold, which is commonly referred to as chattering in literature [78, 79]. Consequently, scholars have directed their attention towards techniques aimed at mitigating chattering, including hybrid or variable-gain SMC as proposed by Ferrara et al. (2002) [80], adaptive SMC as explored by Huang et al. (2008), Plestan et al. (2010), and Utkin et al. (2013) [81, 82, 83], and *higher-order sliding mode* (HOSM) as investigated by Bartolini et al. (1998) and Perez et al. (2020) [84, 85]. The combination of these approaches has the potential to further reduce chattering, as suggested by the works of Shtessel et al. (2012), Pisano et al. (2016), and Incremona et al. (2020) [86, 87, 88].

Various chattering reduction-oriented SMC techniques have been implemented in WECSs that utilize PMSGs. These techniques include hybrid/variable-gain SMC strategies [89, 90] and a second-order *adaptive SMC* (ASMC) strategy for regulating the active and reactive power of the grid-side inverter [91].

To summarize, the utilization of adaptive sliding mode control methods has experienced a growing trend in wind energy conversion systems with the aim of

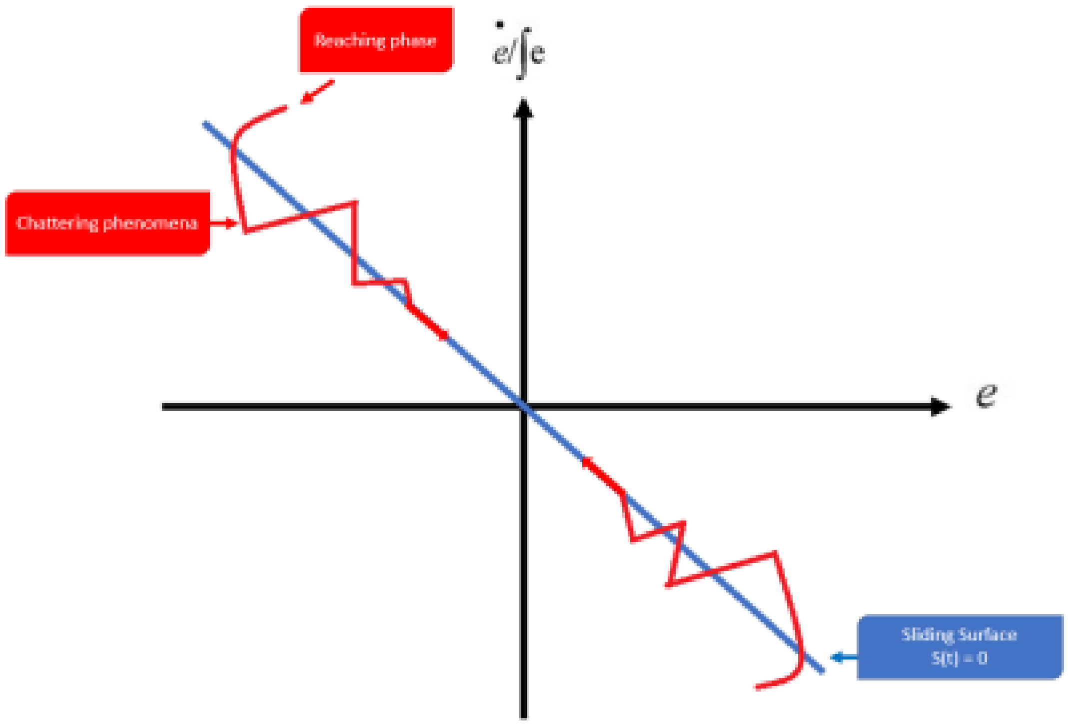

Figure 1.11: Sliding mode control simple scheme. Notations *e* and *e*/ ^{R}*e* - are the tracking error and it is derivative correspondingly.

enhancing their performance, resilience, and durability. Researchers have developed control strategies for PMSG-based WECSs that are more efficient and reliable by concentrating on techniques that reduce chattering, such as hybrid or variable-gain SMC, adaptive SMC, and HOSM.

1.5.3 Model-free control methods in WECS

This section will examine model-free control techniques, which are referred to as data driven control methods in electric drives when they are based on machine learning. Additionally, this section will address the challenges associated with these methods.

1.5.3.1 Fuzzy Logic-Based Control Methods for Electric Drives

The rise in the adoption of machine learning-based controllers in electric drives can be ascribed to their robust control efficacy. The emergence of data-driven control techniques can be attributed to the advancements made in machine learning algorithms and their implementation in diverse industrial domains. Supervised learning algorithms have been effectively employed in the control of motor drives and power electronics, among the various machine learning approaches. Fuzzy logic-based control methods have emerged as a notable illustration, demonstrating their efficacy in managing nonlinear systems and uncertain circumstances, while exhibiting robustness against parameter fluctuations, as evidenced by Bose et al. (2020) [20] in their study on power systems. Fuzzy logic control methodologies are adept at accurately estimating mechanical and electrical parameters, thereby providing significant support to data driven control techniques. However, it is important to note that these methodologies require supplementary control techniques, such as the sliding mode control proposed in [92] or the sliding mode speed observers introduced in [93]. In addition, it has been noted that the effective implementation of fuzzy logic controllers requires the incorporation of feed-forward components in order to enhance their active and reactive control strategies [94].

1.5.3.2 Markov Decision Process-based and Bandit-based Reinforcement Learning Methods

The field of reinforcement learning can be classified into two main branches, namely *Markov Decision Process* (MDP) based techniques and bandit-based approaches. MDP-based model-free algorithms, such as the *Deep Q-Network* (DQN) algorithm, have demonstrated remarkable proficiency in Atari games, surpassing human aptitude (Dong et al., 2020; Mnih et al., 2015; Mnih et al., 2013) [95], [96],[97]. The DQN algorithm faces challenges when applied in continuous spaces, primarily attributable to the exponential growth in dimensionality and the consequent computational load. In order to address this issue, the DQN was enhanced by integrating a deep actor network. This involved replacing the argmax of Q with an actor-critic deep network configuration, resulting in the development of the *deep deterministic policy gradient* (DDPG) algorithm, as described by Lillicrap et al. (2015) [98]. The algorithm in question exhibits a high degree of suitability for addressing intricate problems that involve continuous action spaces with a large number of dimensions, as noted in Sewak et al.'s (2019) [99] research. The algorithm exhibits a remarkable level of performance, however, its internal instability may result in performance fragility. In order to overcome this constraint, an improved variant known as TD3 was proposed, which integrates supplementary target network pairs for both the actor and critic components [100].

1.5.3.3 Deep Reinforcement Learning Applications in Electric Motor Control

The domain of electric drives has seen the application of *Deep Reinforcement*

Learning (DRL) algorithms due to recent advancements in the field. The algorithm's potential was demonstrated in a seminal study by means of a comparison of its performance with that of conventional control techniques in a simulated environment [21]. The Gym toolbox was created with the aim of simplifying the investigation and improvement of DRL algorithms for different motor types and control paradigms in motor drives, as

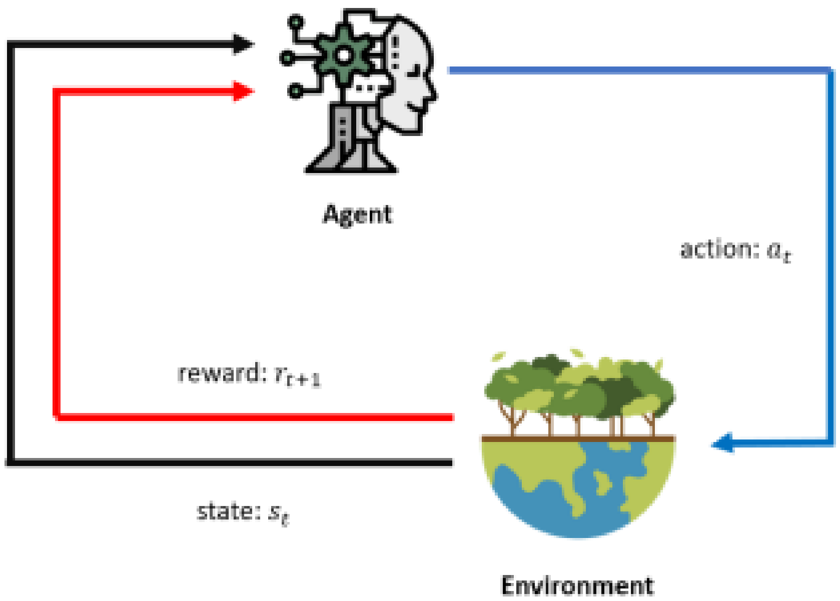

Figure 1.12: Reinforcement learning simple structure

stated by Traue et al. (2020) [101]. DRL has been successfully implemented in the practical application of electric motors, specifically in the context of *permanent magnet synchronous motors* (PMSM), transitioning from its initial use in simulation. The authors of the study utilized a simulation-based approach to train various iterations of the DDPG algorithm, which were subsequently improved upon through experimentation with physical motors [22]. Furthermore, the authors incorporated steady-state error compensation into the DDPG agent to enhance its performance, as reported in Weber et al.'s recent study [102].

1.5.3.4 Further Exploration Advanced DRL Algorithms for Enhanced Motor Control System Performance

The investigation of diverse algorithms has been undertaken in order to enhance the performance of the motor control system. In their study, Nicola et al. (2021) [103] employed the TD3 algorithm to manage the current control loop, while simultaneously preserving *proportional-integral* (PI) control for speed regulation. The study compared the performance of the TD3 agent with a conventional PI controller-based approach. The results showed a significant improvement in response speed during the transient time, ranging from 17 % to 33 %. Previous studies have explored the utilization of the double-clipped quality (Q)-learning algorithm for PMSM current control, as well as the application of the integral Hamilton-Jacobi-based *reinforcement learning* (RL) for PMSM control, which is an off-policy algorithm [104], [105]. The study conducted by Schindler et al. [106] aimed to assess the efficacy of Q-learning, double Q-learning,

and SARSA algorithms in the context of speed control through reinforcement learning. Further investigations have been conducted on the utilization of deep learning for control and performance analysis in machine learning, employing Matlab/Simulink tools as reported in Mishra et al. (2014) [107] and Jin et al. (2017) [108]. It is worth pointing out that in all the above-mentioned work, DRL algorithms are used in purpose to replace the current loop in vector control, but still, an additional speed control loop is required.

1.5.3.5 Reinforcement Learning Implementation in Wind Energy Conversion Systems

In recent times, DRL techniques have been utilized in wind energy conversion systems to achieve diverse objectives. In their study, Venkateswaran and colleagues (2022) [109] employed DRL to determine the optimal rotor speed as a reference signal. This approach enabled the tracking of optimal speed points and maximization of power extraction. The system's main controller utilizes a finite-time control approach and a sensorless control tactic that obviates the necessity for sensors that measure wind speed or tip-speed ratio data. Sivakumar and colleagues (2022) [110] integrated an artificial neural network and reinforcement learning to forecast wind speed and identify optimal operational points, thereby establishing a benchmark angular velocity for pursuing optimal operating points. The Q-learning algorithm was utilized as the reinforcement learning agent in both studies. Subsequent investigations have centred on acquiring knowledge regarding the attainment of optimal *maximum power points* (MPPs) through reinforcement learning techniques. Specifically, Q-learning and *optimal relationship-based* (ORB) control have been implemented to maximize power in wind turbines that utilize PMSGs [111], [112], [113]. The present research employs reinforcement learning as a means to augment the precision of wind turbine control, thereby providing dynamic and accurate reference rotor speed signals to optimize power harvesting. In their recent study, Aghaei and colleagues (2022) [114] presented a novel strategy that substitutes the conventional MPPT technique with a reinforcement learning-based gradient-free Bayesian algorithm. This algorithm, specifically a Markov Chain Monte Carlo algorithm, is designed to compute the load reference current for vertical wind turbines with the aim of optimizing energy production. Moreover, Vu and colleagues (2022) [115] utilized an adaptive optimal fuzzy controller that is grounded on reinforcement learning, as documented in their study. The methodology employed involves the utilization of reinforcement learning to compute the parameters of the adaptive optimal fuzzy controller, thereby facilitating the optimal fuzzy controller for wind turbines based on PMSGs. The works conducted by Aghaei et al. [114] and Vu et al. [115] demonstrate the utilization of reinforcement learning as a supplementary algorithm to bolster the primary controllers.

Table 1.1: Literature review on model-free control methods for electric motor and WECS

Concept	Scheme	Pros	Cons	Ref. No.
Current con trol in an electric motor (PMSM)	Current loop controlled by DRL algorithm namely DDPG.	Model-free control method, self-tuning capability	PI-speed control loop is required	[21], [101], [22], [102]
Current con trol in the Electric motor	Current loop controlled by the DRL algorithm namely TD3.	Implemented TD3 improved DDPG algorithm, thus improved performance of whole tracking performance	PI- speed controller is still required, long train ing process	[103]
Current con trol in Electric motor	Current loop controlled by DRL algorithm namely dou ble clipped Q-learning algo rithm.	Compared with PI controller	PI- speed controller is still required, long train ing process. Simulation only	[104]
Current con trol in Electric motor	Integral RL is implemented to solve the HJB equation online	Works better than the PI con troller	HJB equation should be derived for the plant and then offline trained to es timate weight vectors of HJB. PI- speed controller is required	[105]

Current con trol in Electric motor	Q-learning, Double Q learning, SARSA is implemented as a current loop controller	Compared 3 different DRL algorithms	It is not robust and de pends on random seeds. PI-controller is required for the speed loop. Speed ripple is persistent	[106]
In speed con trol in the elec tric motor	In cascaded PMSM control PI-speed controller is re placed by ANN, but the other two current controllers are left with the PI controller	It is just proved in simulation that it is possible	No performance compar ison, no implementation, 2 PI-current controllers are required	[107]
Performance analysis using DRL	Performance analysis and op timization of permanent mag net synchronous motor based on deep learning	Performance analysis is done for PMSM using DRL	Applied in simulation only	[108]
MPPT for WECS	MPPT is built using the DRL algorithm then the speed tracking process is imple mented using finite-time con trol. Q-learning as DRL used	Improved the performance compared to PI controller	requires model of the plant	[109]

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Concept	Scheme	Pros	Cons	Ref. No.
MPPT for WECS	Integrated an artificial neu ral network and reinforce ment learning to forecast wind speed and identify op timal operational points. Q learning as DRL used	Compared with estimated op timal operational points out performed perturb and ob serve algorithm	operates using model based control	[110]

MPPT for WECS	Integrated an artificial neu ral network and reinforce ment learning to forecast wind speed and identify op timal operational points. Q learning as DRL used. As the MPPT tracking algorithm is used optimal relationship based (ORB) control.	Helps to controller system to obtain the up-to-date optimal relationship between the ro tor speed and output electri cal power of the PMSG.	Whole system still requires knowledge of system parameters, thus model-based controller	[111], [112], [113]
MPPT for WECS	Markov chain Monte Carlo (MCMC) algorithm to opti mize the long-term energy output of a wind turbine and RBFNN as the current con troller.	Model-free	PI-speed controller is re quired, and other two mentioned controller too complex	[114]

MPPT for WECS
The methodology employed involves the utilization of re inforcement learning to com pute the parameters of the adaptive optimal fuzzy con troller, thereby facilitating the optimal fuzzy controller for wind turbines based on PMSGs
Model-free PI-speed controller is re quired, and other con trollers as adaptive opti mal fuzzy control alone with DRL
[115]

1.5.4 Summary of the section control methods

This in-depth analysis investigates various traditional and emerging control methods utilized in WECS, including adaptive and model-free techniques. Historically, traditional control techniques such as PID control, MPC, VOC, and other methods like LQR, LQG, and DTC, have been widely employed to improve the performance of WECS. These tools provide notable advantages in relation to the management of active and reactive power, improvement of energy conversion efficiency, and reduction of dynamic loads. However, the application of these methods is accompanied by several inherent challenges, including the existence of non-linearities within the system, the complexity of computational processes, inaccuracies in the system model, and the presence of additional constraints that are specific to the particular type of turbine generator being used.

The utilization of SMC in WECS has experienced a significant increase due to its inherent characteristics of robustness and resilience. The reduction of high-frequency oscillation, also known as ’chattering’, is a prevalent technique employed in systems such as PMSG-based WECS. Various advancements, such as hybrid or variable-gain SMC, adaptive SMC, and HOSM, have been developed to address these issues.

In recent years, significant advancements have been made in machine learning algorithms, leading researchers to explore control methods that are either model-free or data-driven. Fuzzy logic-based control methodologies have exhibited proficient control capabilities in managing non-linear systems and circumstances distinguished by inherent uncertainty. The application of reinforcement learning techniques, including DQN, DDPG, and the improved TD3, has been shown to yield positive outcomes in the domain of electric drives, leading to significant improvements in response time.

DRL methods have exhibited significant promise in the domain of WECS for achieving a range of objectives. These objectives encompass the identification of the most favourable rotor speed, the prediction of wind speed, and the generation of accurate reference rotor speed signals to enhance power extraction efficiency. In all these mentioned works ascribed as model-free control methods, these data-driven controllers are utilized as a complementary algorithm to gain overall good performance. From Table 1.1 it can be noticed it is the first time model-free control method based on DRL namely the TD3 algorithm implemented as a maximum power point tracking algorithm in WECS. Also in proposed model-free control method replaces all the cascaded control loops which are natural in field-oriented control as well as making the control method more simplified compared to other mentioned model-free control methods, observer-based methods or adaptive control methods.

It is evident that classical control methods continue to play a crucial role in improving the efficiency of WECS. The combination of adaptive and model-free techniques has introduced new possibilities for improving performance and optimizing system operations. Each approach in the field of WECS control systems has its own inherent advantages and obstacles, necessitating continuous research and development in this rapidly evolving domain.

In the subsequent chapters following Chapter 2, we will undertake an exploration of model-free control methodologies centred around DRL, with a particular focus on the TD3 algorithm. Furthermore, after this, it will be provided with a significant understanding of the utilization of ST-ASMC for WECSs based on PMSGs in Chapter 4. The objective of this approach was to furnish the capacity for chattering reduction through the utilization of both HOSM and ASMC, thereby exhibiting its efficacy in a

problem that involves multiple inputs and multiple outputs. A comprehensive simulation study was conducted to compare the ST-ASMC strategy with SMC, ASMC, and an LQR based *integral sliding mode control* (iSMC) method. The assessment of the controllers was conducted by analyzing their capacity to guide the control inputs towards zero while encountering notable fluctuations in stator resistance, stator inductance, and magnetic flux linkage.

1.6 Thesis Outline

This PhD thesis is organized into the following chapters:

Chapter 2 offers a comprehensive analysis of control systems employed in wind turbines, with a specific emphasis on blade control methods such as pitch, yaw, and stall control. This paper elucidates the mathematical principles underpinning the control mechanisms of generators and converters, emphasizing the pivotal role of converters within the WECS. The chapter additionally presents a comparative analysis of different control techniques, including *Field-Oriented Control* (FOC), *Direct Torque Control* (DTC), *Voltage Oriented Control* (VOC), and *Direct Power Control* (DPC). This analysis aims to elucidate the advantages and limitations associated with each technique.

The significance of grid integration is emphasized, accompanied by an examination of grid code adherence and the function of LCL filters. The chapter concludes by examining the *Fault-Ride Through* (FRT) capabilities in wind turbines, providing a comprehensive analysis of the various types of FRT events and their corresponding solutions. The primary objective of this chapter is to offer a thorough comprehension of control techniques for WECS and their practical ramifications.

Chapter 3 Explains the implementation of the model-free control namely *Twin Delayed Deep Deterministic Policy Gradient* called (TD3) algorithm to PMSG-based WECS

Chapter 4 In this chapter comprehensive performance evaluation has been done between LQR and TD3 model-free control method. Then for further performance evaluation purposes, it describes the proposed model-based control design for PMSGs in WECS specifically *super twisting sliding mode control* ST-ASMC, along with the underlying methodology, control methods, and implementation details. The performance of the proposed control strategy is analyzed through extensive simulations and comparisons with existing methods. Discusses a comparison between model-based and model-free control methods in WECS. Summarizes all the results and discusses future work related to the model-free control method

Chapter 5 In conclusion chapter overall performance comparison between model based and model-free control methods is discussed. For each control method inherent characteristics are discussed as robustness and adaptability during uncertainties,

computational complexity and implementation challenges are discussed. Finally, the main contributions of the PhD thesis, limitations and future research direction are provided.

The presented thesis offers a structured exploration of the complexities and challenges of WECS and the potential solutions to address them. This academic endeavour is meticulously segmented into three primary sections:

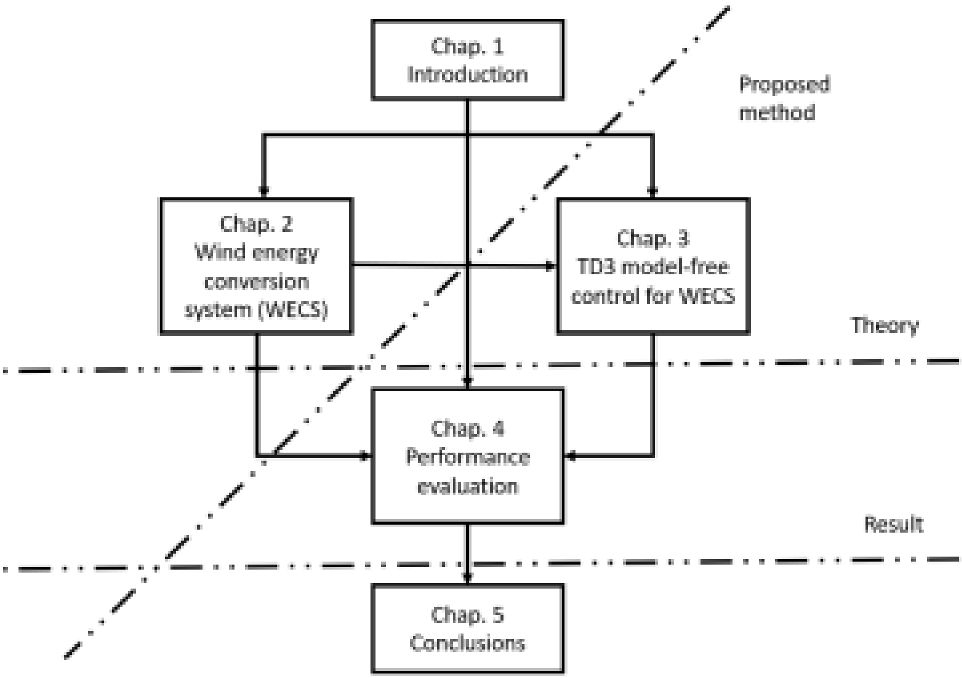

Figure 1.13: Thesis outline in graph

1. Section I: Theoretical Foundations

- This commences with an exposition on the prevailing issues in WECS, subsequently leading to the model-free control solutions designed to mitigate these problems.
- Chapter 2 delves deeper, laying down a comprehensive theoretical framework for understanding the multifaceted aspects of WECS.
- The culminating chapter in this section, Chapter 3, introduces the model free TD3 control method, shedding light on its intricacies and relevance.

2. Section II: Practical Applications

- Chapter 4 serves as the cornerstone of this section, elucidating the application of WECS in simulated environments. Additionally, it

discusses the practical application of model-based control methods in WECS, supplemented by theoretical underpinnings.
- A comparative analysis of these methods, their merits, and potential drawbacks are meticulously delineated in this chapter, offering readers insightful perspectives on their efficacy.

3. Section III: Conclusive Remarks

- This final section synthesizes the extensive discussions from the previous chapters, presenting a concise summary and drawing informed conclu sions on the subject matter.

To assist the discerning reader, chapters situated beneath the illustrative diagonal line provide detailed information on the proposed methods, ensuring a comprehensive understanding of the topic.

1.7 List of publications

1. Zholtayev, D., Rubagotti, M., & Duc Do, T. (2022). Adaptive super-twisting sliding mode control for maximum power point tracking of PMSG-based wind energy conversion systems. *Renewable Energy*, 183, 877-889. Pergamon.

2. Sarsembayev, B., Zholtayev, D., & Duc Do, T. (2022). Maximum power tracking of variable-speed wind energy conversion systems based on a near-optimal servomechanism control system. *Optimal Control*

Applications and Methods, 43(3), 904-924. John Wiley & Sons, Inc.

3. Zholtayev, D. M., & Duc Do, T. (2019, July 20). LQR-Based SMC for Three Phase-Inverter with LC Filter in Renewable Energy Conversion Systems. In *2019 International Conference on System Science and Engineering (ICSSE)* (pp. 456-461). IEEE.

4. Zholtayev, D., Rubagotti, M., & Duc Do, T. (Under review). Model-Free Reinforcement Learning for PMSG Wind Turbine Control via Twin Delayed Deep Deterministic Gradient Descent. *Optimal Control Applications and Methods*.

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Chapter 2

Wind Energy Conversion System

2.1 System components and their models

The fundamental constituents of wind turbines that rely on PMSG technology encompass the wind turbine blades, gearbox, PMSG, power electronic converters, and grid integration systems. The integration of various components facilitates the conversion of wind energy into electrical energy, which is subsequently fed into the grid.

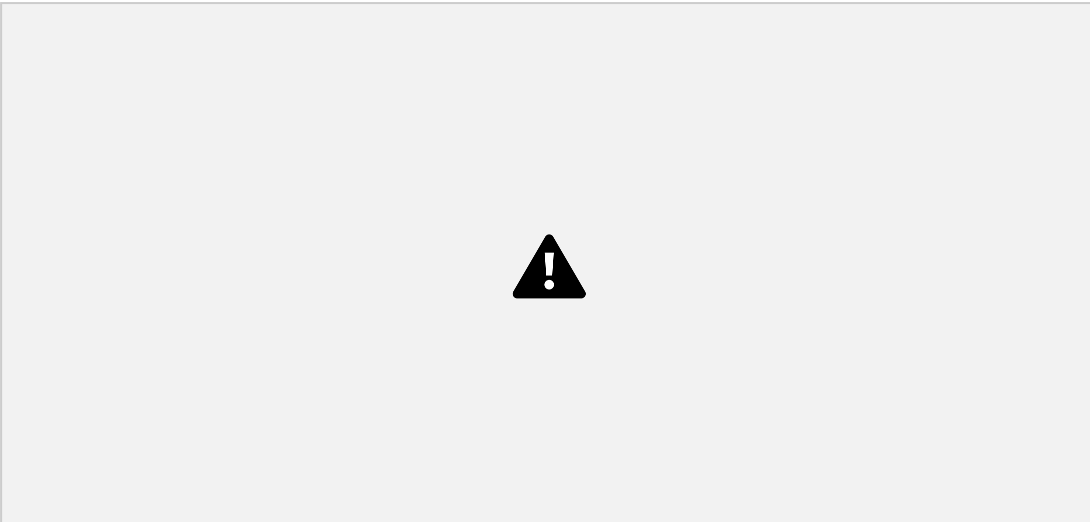

Figure 2.1: Usual configuration of a wind energy conversion system (WECS)

2.1.1 Wind Turbine Model

The energy harnessed by a wind turbine from the wind can be mathematically represented as follows:

$$P_{w}(t) = \frac{1}{2}\rho A C_p(\lambda(t), \beta(t))\, v^3_w(t) \quad (2.1)$$

The equation involves the variable P_w, which represents wind energy, and the symbol ρ, which denotes air density. The variables in the equation are denoted as follows: A

denotes the surface area encompassed by the rotating blades of the wind turbine, C_p represents the coefficient of power, λ pertains to the tip-speed ratio, β is indicative of the blade pitch angle, and v_w signifies the velocity of the wind. The concept of tip-speed ratio, which plays a pivotal role in comprehending the efficacy of wind turbines, is explicated as follows:

$$\lambda(t) = \frac{\omega_t(t)R}{v_w(t)} \quad (2.2)$$

The variable ω_t denotes the angular velocity of the wind turbine, whereas R represents the radius of the blade's rotation.

Moreover, the aerodynamic torque denoted by T_a that operates on the wind turbine can be expressed as:

$$T_a(t) = \frac{1}{2}\rho\pi R^3 C_q(\lambda(t), \beta(t)) v^2_w(t) \quad (2.3)$$

The torque coefficient is represented by $C_q(\lambda(t), \beta(t))$ in the given equation. The correlation between the torque coefficient and the power coefficient is a significant observation, which can be expressed mathematically as follows:

$$C_q(\lambda(t), \beta(t)) = \frac{C_p(\lambda(t), \beta(t))}{\lambda(t)} \quad (2.4)$$

The present equations serve to methodically establish the interdependence among diverse parameters that are fundamental to comprehending the energy harvesting mechanism of wind turbines [116, 117].

2.1.2 Gearbox

The function of the gearbox is to augment the rotational velocity of the rotor to correspond with the requisite velocity of the generator. The determination of the gear ratio can be achieved through the utilization of the subsequent equation:

$$r_{gb} = \frac{n_g}{n_r} \quad (2.5)$$

where r_{gb} is the gear ratio, n_g is the generator speed, and n_r is the rotor speed. The design of wind turbines' gearboxes is a crucial aspect that is influenced by several factors, including the rotor blades' size, mechanical torque, and multiplication ratio, as reported in studies by Yang and Vazquez [118, 119]. The primary function of the gearbox is to transform the low rotational velocity of the rotor into the high rotational velocity that is necessary for the generator to generate electrical energy, as noted in previous studies [120, 121]. The transmission of power from the low-speed rotor to the high-speed generator in traditional wind turbines is accomplished through the utilization of multi-stage fixed-ratio gearboxes, as noted by Mohanty et al. (2018) [122]. The effects of helical gear failure in speed-increasing gearboxes utilized in wind turbine generators have been investigated, as reported in the study by Shanmugasundaram et al. (2014) [123].

Certain wind turbines employ direct-drive generators, which eliminate the need for a gearbox to amplify the rotational velocity of the rotor [124, 125].

2.1.3 PMSG model

2.1.3.1 Dynamic model of PM synchronous machines

Electric machines exhibit the capability to operate as generators or motors depending on the specific context in which they are employed. An illustrative instance is the utilization of PMSM primarily in scenarios that necessitate a variable-speed operation. In situations where a *wind turbine* (WT) provides the mechanical input torque (T_m), the device within a Variable-Speed WECS functions as a generator. As a result, the machine generates power (represented as P_s) or current, which is then transmitted to the three-phase grid through a power converter. In contrast, when functioning as a variable speed motor drive, the machine operates as a motor and converts electrical energy from the grid into electromagnetic torque (T_e), while drawing power (P_s) from the grid. When operating as a generator, the sign of T_m is negative, whereas when functioning as a motor, it is positive. The sign in equation serves to establish the orientation of both the current and power, while the operational characteristics of the machine remain constant. The present thesis maintains consistency with the existing literature by modelling electric machines utilized in WTs as motors. The aforementioned models can be utilized in both generator and motor capacities with the mere modification of the mechanical torque's (T_m) polarity.

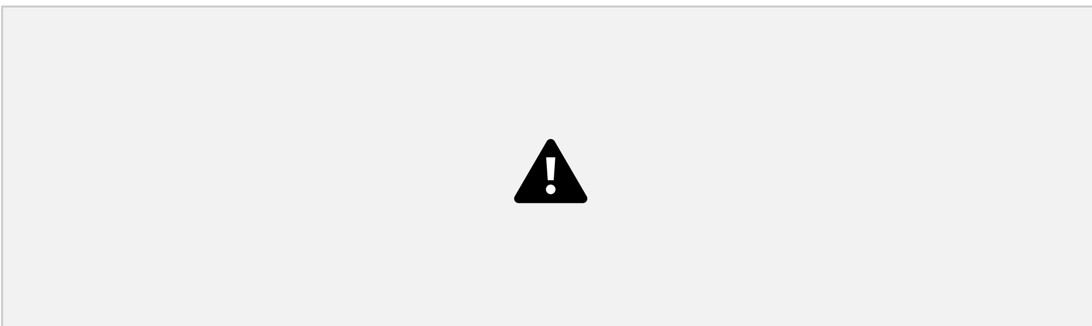

Figure 2.2: PMS machines applications in WECS and vehicles

The governing equation for the dynamics of the rotor mechanical speed can be expressed as:

$$J \frac{d}{dt}\omega_m + b_f \omega_m = T_e - T_m \quad (2.6)$$

Herein, The variable ω_m denotes the mechanical speed of the rotor, measured in radians per second. The variables T_e and T_m represent the electromagnetic and shaft mechanical torques, respectively, measured in Newton meters. The variables J and b_f denote the inertia and viscous friction, respectively, measured in kilograms times meters squared and Newton meters times seconds, respectively.

Negative values are assigned to T_m and T_e in the field of wind energy systems. When considering viscous friction in steady-state operations, it can be observed that T_m exhibits a slightly higher value than T_e. Upon substitution of negative values for T_m and T_e in equation 2.6, the resultant steady-state difference aligns with the observations made in motor control applications. Specifically, the difference between T_e and T_m is equivalent to b_f multiplied by ω_m.

Furthermore, the correlation between the mechanical rotor speed (ω_m) and the electrical rotor speed (ω) can be expressed as follows:

$$\omega_m = \frac{1}{P_p}\omega \quad (2.7)$$

The variable P_p represents the number of pole pairs present in the electrical machine, as specified by the given equation. By combining equations 2.6 and 2.7, the dynamics of the electrical rotor speed can be demonstrated, as elaborated below:

$$\frac{J}{P_p}\frac{d}{dt}\omega + \frac{b_f}{P_p}\omega = T_e - T_m \quad (2.8)$$

This concept can be further streamlined to:

$$\frac{d}{dt}\omega = \frac{P_p}{J}(T_e - T_m) - \frac{b_f}{J}\omega \quad (2.9)$$

Additionally, it is possible to express the rotor position angles in both mechanical and electrical forms.

$$\theta_m = \frac{d}{dt}\omega_m,\ \theta = \frac{d}{dt}\omega,\ \theta_m = \frac{1}{P_p}\theta \quad (2.10)$$

2.1.4 Space vector transformations in electric drives

1. Clarke Transformation:

   The Clarke transformation, which is also referred to as the *αβ* transformation, is a space vector transformation that serves as a crucial tool in streamlining the examination of three-phase circuits. The Clarke transformation is a widely used technique in the field of motor control. Its primary purpose is to convert the three phase stator currents of a motor (i_a, i_b, i_c) into two orthogonal components (i_α, i_β) in a stationary reference frame. The matrix denoting the Clarke transformation is presented as follows:

$$\begin{bmatrix} i_\alpha \\ i_\beta \end{bmatrix} = \begin{bmatrix} \sqrt{2/3} & -\sqrt{1/6} & -\sqrt{1/6} \\ 0 & \sqrt{1/2} & -\sqrt{1/2} \end{bmatrix} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} \tag{2.11}$$

The utilization of a transformation matrix aids in the realignment of the three phase currents into a stationary frame that is two-dimensional in nature. This process enables a more efficient and simplified analysis and management of three-phase systems. The utilization of this technique confers notable benefits, particularly in the domain of motor control, as it facilitates the development of efficacious control tactics for the management of motor currents.

2. Park Transformation:

   The Park transformation, also referred to as the *dq* transformation, is a crucial space vector transformation utilized in the examination and management of three-phase electrical machines. It is credited to Robert H. Park. In contrast to the Clarke transformation, the Park transformation is utilized to transform stationary *αβ* reference frame three-phase quantities into two components within a synchronously rotating reference frame, known as the *dq* reference frame. The formulation of the transformation matrix that represents the Park transformation is as follows:

$$\begin{bmatrix} i_{ds} \\ i_{qs} \end{bmatrix} = \begin{bmatrix} \cos(\theta) & \sin(\theta) \\ -\sin(\theta) & \cos(\theta) \end{bmatrix} \begin{bmatrix} i_\alpha \\ i_\beta \end{bmatrix} \tag{2.12}$$

The aforementioned equation denotes that the variable θ signifies the angular position of the synchronously rotating reference frame in relation to the stationary reference frame.

Comprehending the significance of the Clarke and Park transformations is crucial in the vector control methodology, commonly known as FOC, for AC motors. In essence, the aforementioned transformations serve to facilitate the management of control complexities by efficiently disentangling the regulation of flux and torque in AC motors. The process of decoupling facilitates autonomous regulation of the magnetic field and torque, similar to the control mechanism of *direct current* (DC) motors. This feature is advantageous in terms of enhancing performance optimization and precision of control.

2.1.4.1 Stator voltages in Synchronous frame

The process of transitioning from a *abc* reference frame to a *dq* frame requires a two-step procedure:

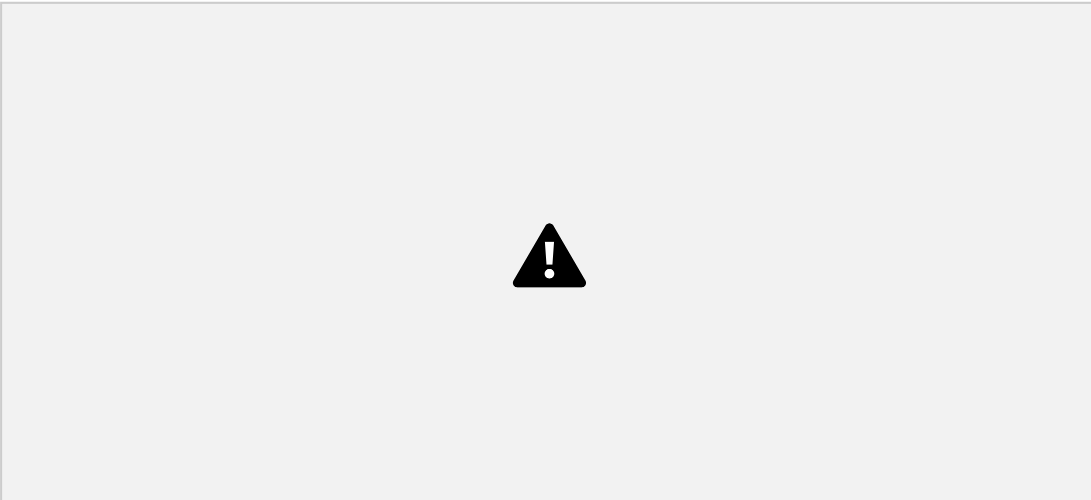

Figure 2.3: Park transformations

1. Initially, the *abc* models undergo conversion to a stationary frame through the application of the *abc* to *αβ* transformation.

2. Subsequently, the models residing in the *αβ* frame are transformed into the *dq* frame by utilizing the *αβ* to *dq* transformation.

After the aforementioned transformations have been carried out, it becomes possible to calculate the stator voltages within the *dq* frame by utilizing the subsequent expression:

$$\mathbf{v} = \mathbf{R_s} \cdot \mathbf{i} + \frac{d}{dt}\psi + \mathbf{M} \cdot \psi \quad (2.13)$$

In this equation:

$$\mathbf{v} = \begin{bmatrix} v_{ds} \\ v_{qs} \end{bmatrix}, \mathbf{R_s} = \begin{bmatrix} R_s & 0 \\ 0 & R_s \end{bmatrix}, \mathbf{i} = \begin{bmatrix} i_{ds} \\ i_{qs} \end{bmatrix}, \psi = \begin{bmatrix} \psi_{ds} \\ \psi_{qs} \end{bmatrix}, \mathbf{M} = \begin{bmatrix} 0 & -\omega \\ \omega & 0 \end{bmatrix}$$

The given variables are as follows: v denotes the stator voltages, R_s denotes the stator resistance matrix, i denotes the stator currents, ψ denotes the stator flux linkages, M denotes the speed voltage matrix, and ω represents the rotor speed.

- v_{ds} and v_{qs} denote the stator voltages of the machine in the dq frame.
- i_{ds} and i_{qs} represent the stator currents of the machine in the dq frame.
- ψ_{ds} and ψ_{qs} are the stator flux linkages of the machine in the *dq* frame.
- ω is the electrical speed of the rotor.

The ultimate term of this equation pertains to the velocity voltages, which are occasionally denoted as induced voltages. It is worth noting that the conversion process from the *αβ* frame to the *dq* frame results in the emergence of velocity voltages in diverse categories of three-phase systems, such as electrical machines, power converters, and harmonic filters.

The aforementioned equation serves as the basis for formulating a conventional model for a PMSM in the *dq* frame. The utilization of this particular model is significant in the examination and regulation of PMSMs through the efficient manipulation of variables in the reference frame that rotates synchronously. This approach offers a more comprehensible comprehension of the machine's dynamics.

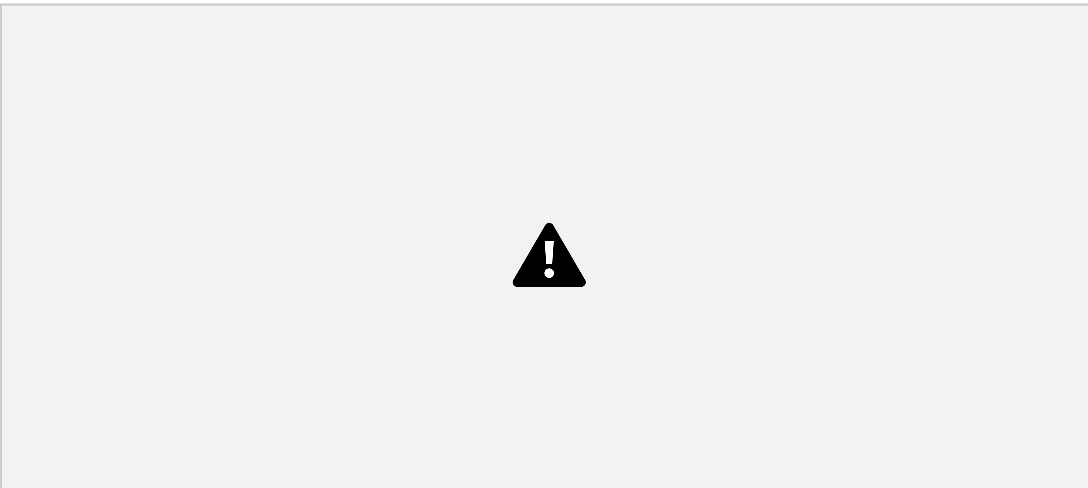

Figure 2.4: Equivalent steady-state circuits and space vector diagram of

2.1.4.2 Stator Flux Linkages in Synchronous Frame

The computation of the machine's flux linkages can be achieved through the utilization of the equation in the *dq* reference frame.

$$\psi = \mathbf{L} \cdot \mathbf{i} + \boldsymbol{\psi}_{\mathbf{r}} \quad (2.14)$$

here $\psi = \begin{bmatrix} \psi_{ds} \\ \psi_{qs} \end{bmatrix}$, $\mathbf{L} = \begin{bmatrix} L_{ds} & 0 \\ 0 & L_{qs} \end{bmatrix}$, $\mathbf{i} = \begin{bmatrix} i_{ds} \\ i_{qs} \end{bmatrix}$, $\boldsymbol{\psi}_{\mathbf{r}} = \begin{bmatrix} \psi_r \\ 0 \end{bmatrix}$

It is imperative to consider the impact of the rotor's electrical position angle, represented by θ_r, on the flux linkages of the rotor and the self and mutual inductance quantities within the machine in the *abc* coordinate system. These parameters are subject to variations as a result of changes in the rotor's electrical position angle. Upon transitioning to the *dq* reference frame, a noteworthy observation arises concerning

the inductance values L_{ds} and L_{qs}, as well as the rotor flux linkage ψ_r, which exhibit constancy over time. The consistent nature of these parameters provides significant advantages by simplifying the analytical procedures involved in both the modelling and administration of PMSMs.

2.1.4.3 Understanding Stator Active and Reactive Power

The purpose of this discourse is to explore the correlation between the apparent power of the stator and the stator voltages and currents in the *dq* domain. The aforementioned association can be expressed in mathematical terms as follows:

$$S_s = P_s + jQ_s = \frac{3}{2}(v_{ds} + jv_{qs})(i_{ds} + ji_{qs}) \quad (2.15)$$

This concept can be further subdivided into:

$$P_s = Re(S_s) = \frac{3}{2}(v_{ds}i_{ds} + v_{qs}i_{qs}) \quad (2.16)$$

$$Q_s = Im(S_s) = \frac{3}{2}(v_{ds}i_{ds} - v_{qs}i_{qs}) \quad (2.17)$$

Upon substitution of the values of v_{ds} and v_{qs} from equation 2.13 into equation 2.16, the expression for the stator active power, denoted as P_s, is obtained.

$$P_s = \frac{3}{2}R_s\left(i^2_{ds} + i^2_{qs}\right) + \frac{3}{2}\left(i_{ds}\frac{d\psi_{ds}}{dt} + i_{qs}\frac{d\psi_{qs}}{dt}\right.$$

$$dt \quad + \frac{3}{2}\omega_r(\psi_{ds}i_{qs} - \psi_{qs}i_{ds}) \quad (2.18)$$

It is noteworthy to mention that the stator active power denoted as P_s is comprised of three distinct components.

- The inaugural term accounts for the Ohmic losses attributed to the stator winding resistance.
- The subsequent term is indicative of the energy stockpiled in the magnetic field.
- The concluding term embodies the air gap power, which is integral to the generation of T_e.

The initial constituent involves the formulation of resistive power, which is derived from the square of the stator currents i_{ds} and i_{qs}. The reactive power, which is the second component, is dependent on the rate of alteration of the stator flux linkages, namely ψ_{ds} and ψ_{qs}. The ultimate component is contingent upon the electrical rotor velocity, denoted as ω_r, in conjunction with the disparity between the product of ψ_{ds} and i_{qs} and the product of ψ_{qs} and i_{ds}.

Conversely, the reactive power of the stator, denoted as Q_s, can be inferred from the following equation, which consists of two complementary elements:

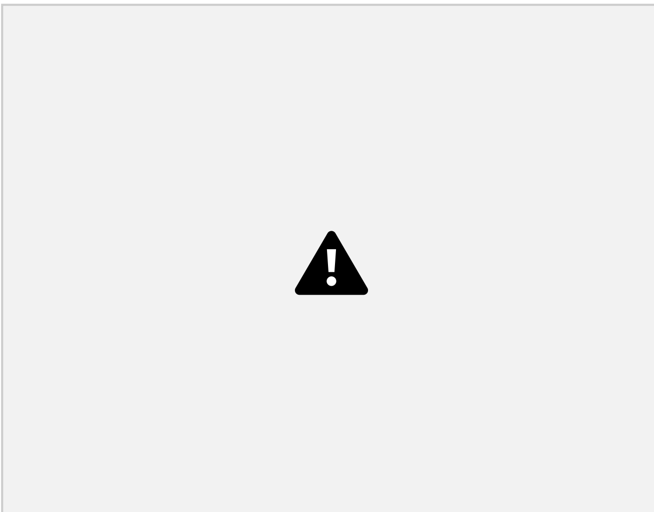

Figure 2.5: Active and reactive power relation with apparent power

$$Q_s = \frac{3}{2}\left(i_{ds}\frac{d\psi_{qs}}{dt} - i_{qs}\frac{d\psi_{ds}}{dt}\right) + \frac{3}{2}\omega_r(\psi_{ds}i_{ds} + \psi_{qs}i_{qs}) \quad (2.19)$$

The foremost element in this context is determined by the temporal alteration of the stator flux linkages, ψ_{ds} and ψ_{qs}, in combination with the stator currents, i_{ds} and i_{qs}. According to Yaramasu's model [126], the secondary component can be expressed as the result of multiplying the electrical rotor speed, denoted as ω_r, by the sum of the products of ψ_{ds} and i_{ds}, and ψ_{qs} and i_{qs}. This information can be found on page 260 of the source.

2.1.4.4 Electromagnetic Torque and Rotor Speed

The mathematical relationship that summarizes the interdependence among the mechanical power of a PMSM, mechanical torque, and speed is as follows:

$$P_m = T_m\omega_m = T_e\omega_r$$

P_p(2.20)

This statement has the potential to be interpreted as:

$$T_e = P_m P_p$$

ω_r(2.21)

By incorporating the third segment originating from equation 2.18, which is a result of the formation of T_e, into equation 2.21, the electromagnetic torque can be obtained in the following manner:

$$T_e = 3P_p$$

$2(\psi_{ds} i_{qs} - \psi_{qs} i_{ds})$ (2.22)

Through the incorporation of the values of ψ_{ds} and ψ_{qs} as stated in equation 2.14 into equation 2.22, an outcome is derived.

$$T_e = 3P_p$$

$2[\psi_r i_{qs} + (L_{ds} - L_{qs}) i_{ds} i_{qs}]$ (2.23)

Consequently, the integration of this equation into the initial correlation

results in: $dt = 3P^2{}_p$

$2J\psi_r i_{qs} + 3P^2{}_p$

$d\omega$

$2J(L_{ds} - L_{qs}) i_{ds} i_{qs} - P_p$

$J T_m - B_m$

$J\omega$ (2.24)

The dynamics of rotor speed are comprehensively characterized by the equation presented in [126] on page 188.

2.1.4.5 PMSG model in ***dq*** frame

The model of the Permanent Magnet Synchronous Generator (PMSG) in the *dq* reference frame is represented by the following equations:

$$\frac{d\omega(t)}{dt} = \frac{1}{J}\left(-b_f\omega(t) - T_e(t) + T_m(t)\right) \quad (2.25)$$

$$\frac{di_{qs}(t)}{dt} = -\frac{R_s}{L_s}i_{qs}(t) - P_p\omega(t)i_{ds}(t) - \frac{\psi_m P_p}{L_s}\omega(t) + \frac{1}{L_s}v_{qs}(t) \quad (2.26)$$

$$\frac{di_{ds}(t)}{dt} = -\frac{R_s}{L_s}i_{ds}(t) + P_p\omega(t)i_{qs}(t) - \frac{\psi_m P_p}{L_s}\omega(t) + \frac{1}{L_s}v_{ds}(t) \quad (2.27)$$

The equations presented herein elucidate the dynamics of the rotor speed and stator currents in the *dq* frame. The electromagnetic torque, denoted as T_e, is a crucial parameter that can be expressed as follows:

$$T_e(t) = K_T\, i_{qs}(t) \quad (2.28)$$

The variable K_T represents the torque constant of the generator, which can be expressed as $K_T = \frac{3}{2}\psi_m P_p$.

Equipped with these models, an individual can exert authority over both the wind turbine and the electric motor based on PMSG. The implementation of this control mechanism is crucial in achieving optimal power extraction and ensuring consistent operational stability. The effective realization of these objectives is significantly dependent on the management of the generator-side converter.

Remark: Surface PMSG (SPMSG) is usually considered more powerful and complex than, interior PMSG (IPMSG). For SPMSMs, the mathematical model is relatively simpler compared to IPMSMs because the magnetic field is largely aligned with the rotor and there is minimal saliency (difference between d-axis and q-axis inductances) which is usually considered as $L_{ds} = L_{qs}$, as a consequence dynamic equation simplifies. The main difference in equations arises due to the rotor saliency in IPMSMs, which leads to different d-axis and q-axis inductances $L_{ds} \neq L_{qs}$. This introduces an additional reluctance torque term in the equation for electromagnetic torque T_e. In equations 2.25

- 2.27 presented dynamic equation for SPMSG. In further our discussion when we talk about PMSG, by default we referring to SPMSG. Then L_{ds}, L_{qs} conventions becomes just L_s.

2.1.5 Power Electronic Converters

Power electronic converters are utilized to establish a connection between the PMSG and the grid. The converters are responsible for regulating the voltage and current output of the generator to ensure that the power extraction is optimized and that the integration with the grid is seamless. The converters are comprised of two primary constituents, namely the converter situated on the generator side and the converter located on the grid side.

2.1.5.1 Machine-side Converter

The primary objective of the *Grid-Side Converter* (GSC) is to regulate the net DC-bus voltage, represented as v_{dc}, to ensure its conformity with the desired reference value v^*_{dc}. Additionally, the GSC is responsible for generating reactive power Q_g in accordance with the prescribed directive Q^*_gissued by the grid operator. The block diagram depicts the process of calculating the reference currents for the abc-, *αβ*-, and *dq*-frames, which include the references for grid active and reactive power. It should be noted that the generator-side control for the MPPT is taken into consideration.

The formulation of the reference d-axis grid current, denoted as i^*_{dg}, involves the utilization of a PI controller. The aforementioned controller ensures that the measured DC-bus voltage, represented as v_{dc}, is in agreement with its designated reference value, v^*_{dc}.

The function of the PI controller can be expressed mathematically as follows: $C(s) = k_p + \frac{k_i}{s}$ Here, s denotes the Laplace operator and k_p and k_i represent the proportional and integral gains, respectively.

$$i^*_{dg} = \left(k_p + \frac{k_i}{s}\right)(v^*_{dc} - v_{dc}) \quad (2.29)$$

In the GSC context, under the assumption of a lossless scenario, the active power on the AC side denoted as P_g is equivalent to the DC power.

$$P_g = 1.5 v_{dg} i_{dg} = v_{dc} i_{dc} \quad (2.30)$$

The output value of $i^*_{dg}(k)$, as produced by the PI controller, is influenced by fluctuations in operational parameters. The *Machine-Side Converter* (MSC) is an integral component of the WECS that regulates the current i_{dc} to optimize the extraction of wind energy. When the WT operates at wind speeds below its cut-in threshold, the MSC generates a zero i_{dc}. At the rated wind speed, the rated value of i_{dc} is attained

during the operation of the WT. A fluctuating direct current source is postulated for the purpose of modelling a variable-speed wind energy conversion system. The grid operator provides the reference reactive power command denoted as Q^*_g. The value can be adjusted to zero to achieve unity, a negative value to attain a leading power factor, or a positive value to achieve a lagging power factor. The q-axis reference grid current, represented by i^*_{qg}, can be inferred from Q^*_g as demonstrated:

$$i^*_{qg} = \frac{Q^*_g}{-1.5 v_{dg}} \quad (2.31)$$

Transformation matrices are utilized to convert the reference currents in the *dq* frame into the *αβ* and *abc* frames.

The determination of the reference grid active power P^*_g involves the multiplication of i^*dg and *vdc*, as stated in page 260 of the work by Yaramasu et al. (2016) [126].

2.1.5.2 Grid-side Converter

The *Grid Side Converter* (GSC) plays a crucial role in facilitating the connection between the electrical grid and the wind energy conversion system. The system carefully regulates the transfer of both active and reactive power to and from the grid, guaranteeing adherence to the grid's standards for voltage, frequency, and power integrity. The equations presented below offer a mathematical depiction of the control mechanism governing the grid-side converter:

$$P_g = \frac{3}{2}(v_{gd} i_{gd} + v_{gq} i_{gq}) \quad (2.32)$$

$$Q_g = \frac{3}{2}(v_{gd} i_{gq} - v_{gq} i_{gd}) \quad (2.33)$$

The terms in the equations are as follows:

- P_g: Active power that is supplied to the grid.
- Q_g: Reactive power that is exchanged with the grid.
- v_{gd} and v_{gq}: The d-axis and q-axis components, respectively, of the grid voltage. • i_{gd} and i_{gq}: The d-axis and q-axis components, respectively, of

the grid current.

The aforementioned equations establish a connection between the voltage and current components in the *dq* frame and the active as well as reactive power supplied to the grid. The effective management of these quantities is crucial for maintaining the stable and efficient functioning of wind energy conversion systems, as well as for facilitating their seamless integration into the power grid, as noted by Yaramasu et al. (2016) [126] on page 253 of their publication.

2.1.6 DC-Link

The DC-bus, commonly referred to as the DC-link, plays a pivotal role as an intermediary stage between the converter on the generator side and the converter on the grid side in wind energy systems. The inclusion of a DC-bus capacitor and, in some cases, a DC-DC converter, serves as a means to enhance the dependability and effectiveness of the system.

Energy Storage and Power Regulation: The DC-link is a crucial energy storage medium that facilitates power flow between the generator-side and grid-side converters. It is responsible for storing excess power and releasing it during periods of power shortages, making it an essential component of the energy system [127]. The significance of this mechanism lies in its ability to address the uncertain and variable characteristics of wind resources. The DC-link, when combined with energy storage systems such as battery energy storage systems and supercapacitors on a large scale, has the ability to stabilize power quality and manage both average and transient power demands that arise due to load fluctuations, renewable energy variability, and fault conditions [128, 129]. According to Junyent et al. (2014) [130], the integration of DC link and wind turbines can offer swift primary frequency control and system inertia to an AC network. The implementation of this approach guarantees dependable electricity production, particularly when confronted with fluctuating wind and solar power sources [128]. Furthermore, by means of the synchronized management of the DC-link voltage and pitch angle within wind energy conversion systems, the generated power can be efficiently stabilized [131].

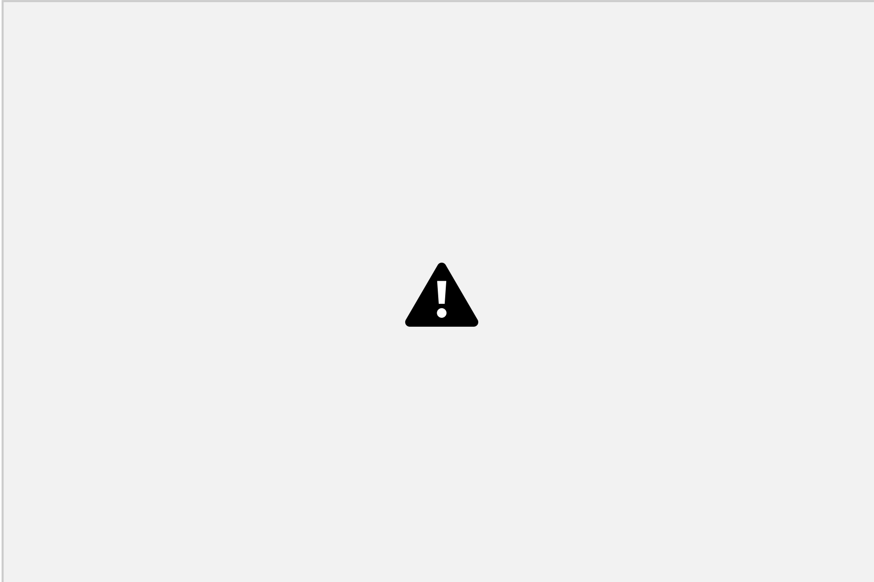

Figure 2.6: DC-link energy storage and isolation components

Isolation and Protection: The DC-link plays a crucial role in providing isolation between the machine MSC and GSC, thereby enabling the wind turbine to operate at

variable speeds. This feature is of utmost importance for achieving MPPT, as evidenced by studies conducted by Laghridat et al. (2019), Li et al. (2021), and Singh et al. (2021) [132, 133, 134]. According to Worku et al. (2015) [135], the isolation also serves as a protective measure against potential malfunctions that may arise from either the wind turbine or synchronous generator components. The management of the DC-link voltage enables the achievement of voltage regulation on both sides of the converter, as noted in previous studies [136, 133, 137].

Design Considerations: The performance, efficiency, and cost of the wind turbine system are significantly influenced by the design elements of the DC-link, such as the DC-link capacitor's sizing and the incorporation of a DC-DC converter. According to Okedu et al. (2020) [138], research has demonstrated that the implementation of a DC-link scheme utilizing parallel capacitors can improve the response of grid voltage in the event of severe grid faults. According to Jedtberg (2017) [139], the lifespan of the DC-link capacitor can be reduced by low-frequency ripple current components. As per Lukasievicz's proposed control methodology for wind generation units, it is feasible to regulate the DC-link voltage without the need for a battery bank or ultra-capacitor [140]. The DC-link serves as a protective measure for the system against any potential malfunctions that may occur on the wind turbine or synchronous generator end, as noted by Haidar et al. (2017) [141] in their study on coordinated systems.

The present summary elucidates the pivotal functions that the DC-link performs in the domains of energy storage and regulation, isolation, and safeguarding while delineating the noteworthy aspects of its design. Efficient wind energy systems' research and development places significant emphasis on the DC-link.

2.2 Control aspects in wind energy conversion system of different components

2.2.1 Pitch Control

Pitch Control System and Blade Angle: The management of rotor speed and power output in a wind turbine is contingent upon the pitch control system, which operates by regulating the angle of the blades. This system is of utmost importance to the overall functionality of the turbine. The system additionally provides protection to the turbine against mechanical harm during high wind circumstances through blade feathering. The power coefficient function, $C_p(\lambda, \beta)$, is reliant on the blade pitch angle, denoted as (β), as per Goupee's research in 2017 [142].

Feedback Mechanism and Control Strategy: The pitch control system functions through a feedback mechanism that consistently monitors the speed of the rotor and juxtaposes it with a reference speed. The reduction of the difference between the

aforementioned values is achieved through the implementation of a PI control approach. The aforementioned system is designed to adjust the pitch angle in response to the control signal, with the aim of maintaining the rotor speed within the optimal range, as stated in Nielsen's work [143]. Schena (2022) [144] notes that conventional controllers, which operate based on blade pitch and yaw angles or generator torque, typically employ PID controllers.

Power Output Regulation: The management of a wind turbine's power output is reliant on the pitch control system. According to Chaudhary (2015) [145], the system is designed to maintain a consistent angle of the rotor blades within the wind speed range that falls between the cut-in and rated speed. This approach is aimed at optimizing the capture of energy. When wind velocity surpasses the designated threshold, the pitch control mechanism adjusts the angle of the blades in order to restrict the mechanical energy harnessed by the rotor to its predetermined capacity. The implementation of this particular approach serves to mitigate the risk of the turbine exceeding its electrical power generation capacity, thereby safeguarding the generator and power electronics against the possibility of overloads [146][147]. According to Liu (2022), the implementation of efficient techniques can mitigate the variability of generator speed at or below the rated wind speed.

Feathering and Shutdown Procedures: When wind speeds surpass the cut-out speed, the pitch control system adjusts the blades to an almost perpendicular angle with respect to the wind. The implementation of the ’feathering’ or ’flagging’ technique results in a reduction of the wind’s force on the blades, leading to the cessation of rotor motion and providing protection to the wind turbine against potential damage. The pitch-to-feather control method is a widely employed approach for limiting wind turbine power generation during high wind speed scenarios. This technique involves executing an emergency shutdown by rapidly adjusting the blade pitch to a feathered position, as described in previous studies [148][149]. According to Jiang et al. (2015) [150], blade pitching takes place during the shutdown of pitch-regulated turbines, and in the event of a pitch actuator failure, a one- or two-blade shutdown may ensue. Passive pitch control is a commonly employed safety measure in micro- and mini-wind turbines, as reported by Vila et al. (2021) [151] in their study on turbine design.

2.2.2 Yaw Control

The function of the yaw control system in wind turbines is to optimize power capture by aligning the turbine rotor plane with the incoming wind. The system comprises a yaw motor and a control module that gauges wind direction via wind vanes and juxtaposes it with the orientation of the turbine rotor. In the event that the discrepancy surpasses a pre-established deadband, the control module issues a directive to the yaw motor to initiate rotation of the nacelle, thereby aligning it with the prevailing

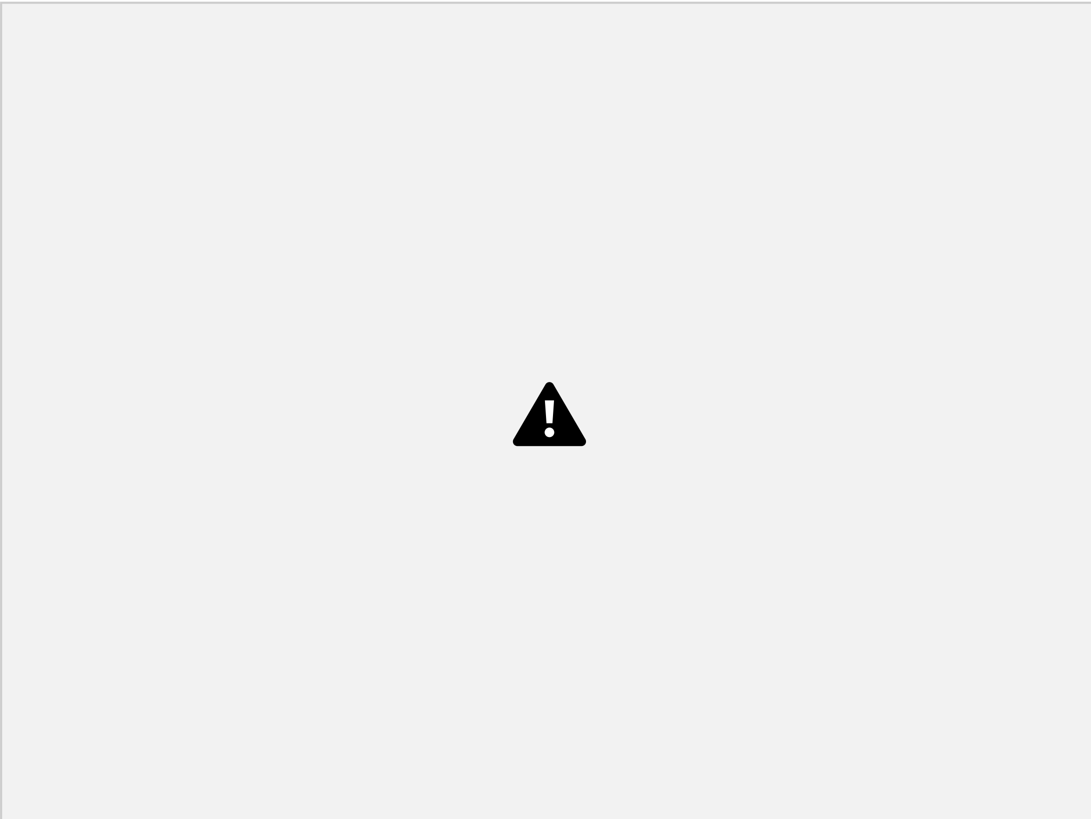

Figure 2.7: Yaw and pitch control in wind turbine

wind direction. The aerodynamic model of a wind turbine incorporates the yaw angle, which has the potential to impact the power coefficient (C_p) as per Bastankhah and Porté-Agel's research [152]. According to Jin's numerical study (2023) [153], there is a positive correlation between the magnitude of the yaw angle and the amplitude of the fluctuation. According to Hermawan's research on wind turbines, it has been observed that horizontal axis wind turbines require alignment with the direction of the wind flow, whereas vertical axis wind turbines do not necessitate such alignment [154]. In recent years, there has been a sustained interest in the approach of regulating the yaw angles of the upstream wind turbine in order to mitigate the impact on the downstream turbines, as noted in a study by Fan et al. (2023) [155]. The wind turbine control system relies heavily on the yaw system, with yaw error serving as a crucial performance metric that significantly impacts power generation [156].

2.2.3 Stall Control

The implementation of stall control is a passive technique employed in wind turbines with the aim of constraining power generation during periods of elevated wind velocities. The attainment of this objective is accomplished through the strategic design of the blades, which are engineered to enter an aerodynamic stall state upon the attainment of a specific threshold wind speed, commonly referred to as the rated wind speed. According to Bastankhah and Porté-Agel (2019) [152], the implementation of stall control can mitigate the fore-aft tower loading and blades flapwise moment in wind turbines equipped with stall-regulated blades, specifically in uniform wind conditions. Wind turbines are often subject to sudden fluctuations of wind direction and velocity when operating in complex field environments (Jin, 2023) [153]. The application of either active or passive stall control can be implemented in wind turbines, as noted by Hermawan et al. (2023) [154]. The optimization of wind turbine technologies for domestic use is hindered by their high implementation costs [156].

2.2.4 Maximum Power Point Tracking control

The variability of wind power extraction by a turbine is contingent upon multiple factors, including but not limited to wind velocity, atmospheric density, and turbine specifications. The primary objective of MPPT is to optimize the operational parameters of the turbine to consistently achieve the highest attainable power output.

2.2.4.1 Machine-Side control

The MPPT algorithm continuously monitors the wind speed and adjusts the rotor speed to align with the optimal tip-speed ratio, represented as λ_{opt}. The formula that expresses the relationship governing this adjustment is as follows:

$$\omega_{\mathrm{ref}}(t) = \frac{\lambda_{opt} v_w(t)}{R} \tag{2.34}$$

The implementation of this technique guarantees that the wind turbine consistently operates at its maximum power output, leading to a substantial increase in the overall efficiency of the wind energy conversion system.

In order to devise a control strategy for the converter located on the generator's side, it is feasible to utilize the following dynamic equations, which are further logical evolution of equations derived from 2.25 - 2.27:

$$\frac{d\omega(t)}{dt} = \frac{1}{J}\left(-b_f\omega(t) - T_e(t) + \frac{1}{r_{gb}} T_a(t)\right) \tag{2.35}$$

$dT_e(t)$

$dt = -R_s$

$L_s T_e(t) - P_p K_T \omega(t) i_{ds}(t) - \psi_m P_p K_T$

$L_s \omega(t) + K_T$

$L_s v_{qs}(t) + d_{qs}(t)$ (2.36)

$di_{ds}(t)$

$dt = -R_s$

$L_s i_{ds}(t) + P_p$

$K_T \omega(t) T_e(t) + {}^{1} L_s v_{ds}(t) + d_{ds}(t)$ (2.37)

The variable r_{gb} denotes the gearbox ratio, whereas d_{ds} and d_{qs} represent perturbation components that encapsulate modelling inaccuracies, uncertainties, and fluctuations in the attributes of the electrical components.

The implementation of a control methodology, specifically vector control, can effectively regulate the d-axis and q-axis currents (i_{ds} and i_{qs}) and voltages (v_{ds} and v_{qs}) to maintain the desired generator speed and maximize power extraction. The vector control approach typically involves setting the d-axis current, represented by i_{ds}, to zero, while adjusting the q-axis current, denoted as i_{qs}, to emulate a predetermined reference value based on the desired generator speed and torque.

By skillfully managing the converter located on the generator side, the wind energy conversion system can operate with optimal efficiency and generate the highest possible power output based on the current wind speed. This is achieved while maintaining stability and adhering to the requirements for integrating with the power grid.

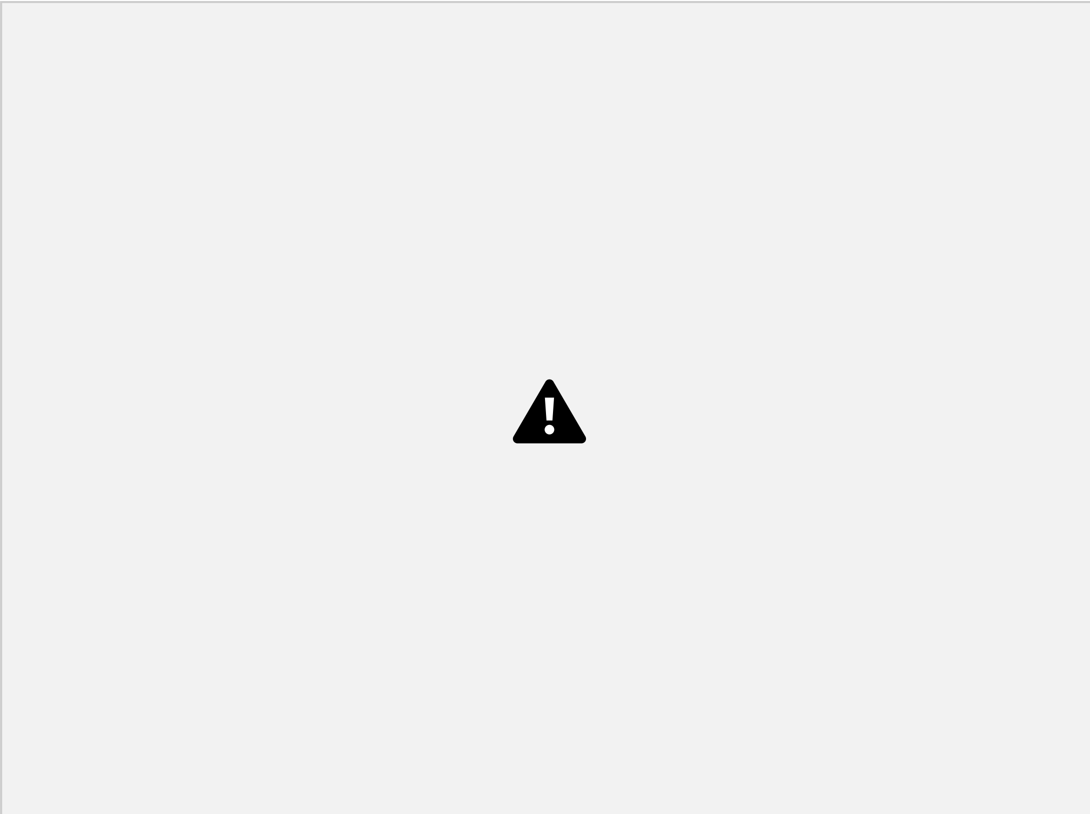

Figure 2.8: Block diagram of the overall digital control system in type 4 wind power conversion system

2.2.5 Vector Control or Field-oriented control and Direct power control classical control methods

- FOC and DTC control comparison: This study presents a comparative analysis of the efficacy of FOC and DTC when implemented in the generator-side converter of Direct Drive Wind Turbines. The manipulation of rotor speed in FOC is

achieved through the regulation of electromagnetic torque. On the other hand, DTC utilizes a predetermined switching table that is influenced by the hysteresis control of stator flux linkage and torque to select appropriate voltage vectors. The efficacy of FOC and DTC is assessed using various parameters such as steady-state and transient performances, low-voltage ride-through capabilities, power limitation, and reactive power control. It is noteworthy that the steady-state performance of FOC is superior, albeit its dynamic response is comparatively inferior to that of DTC.

- VOC and DPC control comparison: The Direct Drive Wind Turbine grid-side converter is subject to a comparison between VOC and DPC. The utilization of VOC as a technique for controlling vectors has been found to offer exceptional power quality characteristics. In comparison, the DPC method exhibits superior dynamic response and reduced power cross-coupling, as a direct control approach. Although both methods do not result in wind turbine tripping in the event of a fault, vector control yields reduced power oscillations.

- FOC advantages over DTC: The FOC technique offers several benefits such as the ability to precisely control rotor speed through the manipulation of electromagnetic torque, superior steady-state performance in comparison to DTC, reduced torque ripple, lower *Total Harmonic Distortion* (THD) of current, enhanced tracking error, and a diminished cross-coupling effect. Nevertheless, the technology exhibits certain limitations, including a comparatively sluggish dynamic response in contrast to DTC, as well as a requirement for more intricate control algorithms and hardware implementation.

- DPC advantages over VOC: The advantages of DPC encompass expeditious and dynamic responsiveness, reduced power cross-coupling in comparison to VOC, and a straightforward control framework that obviates the need for coordinate transformation. In addition, it has the capability to control reactive power through the establishment of a reference value of zero for reactive power, leading to the attainment of power factor unity during operation.

- DTC disadvantages: On the other hand, it should be noted that DTC exhibits certain drawbacks such as increased torque ripple and current THD in comparison to FOC, as well as substandard steady-state performance. In addition, it requires more intricate control algorithms and hardware implementation compared to FOC. [157, 158].

2.2.6 Filters and Grid Code Compliance

The presented literature underscores the importance of adhering to grid code regulations for megawatt-scale wind turbines that are connected to the power grid. The task of meeting the aforementioned requirement falls on power converters, which are required to supply currents to the grid with minimal THD, provide reactive power upon request by the grid operator, maintain operation during grid faults, and provide voltage/frequency support, among other responsibilities. The objective is to accomplish this exclusively through the utilization of the power converter, without depending on external hardware or components such as *STATic synchronous COMpensator* (STATCOM) (A rapidly responsive apparatus with the ability to deliver or absorb reactive current, thereby effectively controlling the voltage at the point of interconnection with an electrical power grid) or FACTS.

- Role of LCL Filters: To comply with the grid codes, it is necessary to implement LCL filters on the grid side, which effectively reduces the overall harmonic distortion present in the current. The LCL filter located on the grid side produces an output that is subsequently transmitted through three-phase AC cables to the step-up transformer situated at the substation. The LCL or L harmonic filters have become increasingly prominent in wind energy conversion systems owing to their ability to alleviate harmonic effects on the grid. The devices are designed to mitigate the harmonic distortion generated by the power electronics within the system. This distortion has the potential to cause unwanted distortions in voltage and current waveforms, which would violate grid codes.

- Grid Codes and Compliance: The grid codes refer to a collection of technical requirements that govern the integration of renewable energy systems into the power grid. Ensuring compliance with these regulations is of utmost importance in order to ensure the secure and reliable operation of the power grid. Wind energy conversion systems are required to adhere to rigorous guidelines pertaining to harmonic distortion levels. To achieve compliance, these systems commonly integrate the utilization of LCL or L harmonic filters in conjunction with control methodologies such as model predictive control. The amalgamation of these components facilitates the mitigation of harmonic distortion levels, thereby ensuring adherence to grid code regulations.

- Implementation and Challenges: The comprehensive power converter assembly, comprising the LC filter on the generator side, *Voltage Source Rectifier* (VSR), DC link, *Voltage Source Inverter* (VSI), and the harmonic filter on the grid side, is contained within a solitary cabinet situated in the nacelle. The implementation of an LC filter on the generator side is employed to mitigate the adverse effects of harmonic distortion present in the generator currents. The LCL filter situated on the grid side produces an output that is subsequently transmitted through three-phase AC cables to the step-up transformer positioned at the tower's base. Notwithstanding their practicality, AC cables incur considerable expenses and inefficiencies as a result of their *Low-Voltage* (LV) rating and high current usage. It is worth noting that the converters are reasonably priced owing to the advantages of mass production, as indicated by Yaramasu in his studies [126, 10].

2.2.7 Fault-Ride Through Capability

The ability to maintain connectivity and operation during grid faults, commonly referred to as FRT capability, is a crucial characteristic of wind turbines. The incorporation of this characteristic is of utmost importance in guaranteeing the consistency and dependability of the power infrastructure and is a requirement stipulated by the grid codes of numerous nations.

- Types of FRT Events: The capacity of FRT is determined by the nature of voltage perturbations, namely dips or swells, that may arise during grid malfunctions. The voltage occurrences are classified as *zero-voltage ride-through* (ZVRT), *low-voltage ride-through* (LVRT), and *high-voltage ride-through* (HVRT). In the context of power systems, ZVRT events are characterized by a complete loss of grid voltage, whereas LVRT events are characterized by a voltage dip ranging from 15-25% of the nominal value of the grid voltage. HVRT events are indicative of occurrences of voltage surges in the power grid. .

- Achieving FRT Capability:There are multiple approaches available for achiev ing FRT proficiency. Potential solutions encompass the utilization of energy storage systems, power electronics-oriented alternatives such as STATCOMs or *A Static Var Compensators* SVCs (The purpose of employing this technology is to enhance the voltage stability of the system and augment the LVRT capability of the wind farm), or the implementation of specialized control methodologies for wind turbines. The development and execution of FRT solutions are subject to various factors, including the type of wind turbine generator, the scale of the wind farm, and the particular grid code specifications.

- Grid Code Specifications: The voltage dips or swells that a wind turbine must be capable of withstanding during grid faults are specified by grid codes, which exhibit variability across different nations. In addition to ZVRT, LVRT, and HVRT events, certain grid codes delineate additional types of incidents, such as

voltage asymmetry and fluctuations in frequency. The FRT requirements may vary depending on the wind farm's size and its position within the power system.

- Solutions for FRT Capability: A diverse range of solutions can be employed by wind turbines to attain FRT capability. Energy storage systems have the ability to furnish a transient energy supply in the event of voltage dips or swells. Power electronics-based solutions can provide swift reactive power support to sustain voltage stability during grid faults. Furthermore, specialized control strategies can enable wind turbines to endure voltage dips or swells by adjusting their active and reactive power outputs.

- Considerations for FRT Solutions: The development and execution of FRT solutions are contingent upon a multitude of factors, including the type of wind turbine generator, the scale of the wind farm, and the particular mandates outlined in the grid code. Hence, it is imperative for wind turbine manufacturers and operators to meticulously contemplate these aspects while devising and executing FRT (Fault Ride Through) resolutions [10, 126].

2.3 Summary

The present chapter offers a comprehensive survey of the constituent parts and management tactics that are crucial to a wind turbine system that relies on a PMSG. The text identifies crucial components, namely the wind turbine blades, the generator, the DC-link, and the grid-side converter.

- Blade Control Techniques: The primary emphasis is on the implementation of blade control techniques, including yaw, pitch, and stall control methodologies. The utilization of these techniques holds significant importance in optimizing the extraction of wind energy and ensuring the secure and effective operation of the turbine across diverse wind circumstances.

- Machine-side Control: Subsequently, the chapter proceeds to explore the control mechanism of the generator and the strategy of MPPT. The aforementioned methodology modifies the torque and speed of the generator to attain optimal efficiency across a range of wind velocities.

- Grid-side Control: Subsequently, the discourse shifts towards grid-side control, which pertains to the preservation of the calibre and steadiness of the power that is infused into the grid.

- Grid Integration Aspects: The article emphasizes essential aspects of grid integration, including synchronization and adherence to grid code standards. These components guarantee that the power generation of the wind turbine conforms to the standards and regulations of the grid.

- Wind Energy Conversion System Control Techniques: This literature review examines essential control methodologies, such as FOC and DTC. The employment of these methodologies enables accurate and autonomous manipulation of crucial variables, thereby promoting the optimal and adaptive functioning of the system.

- Mathematical Techniques: The concluding section of the chapter provides a summary of mathematical methodologies, including Clarke and Park transforma tions. The process of converting three-phase quantities into two-phase quantities in a rotating frame is known to simplify the control problem. This conversion technique renders the system more amenable to analysis and facilitates control design.

This chapter offers a thorough comprehension of wind turbine control facets, encompassing blade control and grid integration, and establishes a basis for the forthcoming design and execution of sophisticated control tactics for wind turbines based on PMSG.

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Chapter 3

TD3 Model-Free Control Method for Wind Energy Power Conversion System

3.1 Reinforcement learning, deep reinforcement learning and control

3.1.1 Introduction

The optimization of wind turbine performance necessitates precise control of the com plex systems involved. The utilization of model-based control methodologies has been extensively employed in the control systems of wind turbines. Notwithstanding, these methodologies encounter various obstacles, including the intricacy of precisely mod elling the wind turbine's nonlinear and time-varying dynamics [159]. Furthermore, control methodologies based on models necessitate a substantial allocation of computa tional resources, posing a potential obstacle for real-time control implementations.

As a means of addressing these obstacles, the utilization of model-free RL has been put forth as a viable alternative strategy for wind turbine management. RL is a machine learning paradigm that facilitates the acquisition of optimal control policies by an agent through iterative interactions with the environment, wherein the agent learns from its successes and failures [160]. RL has the advantage of being applicable to nonlinear and time-varying systems, such as wind turbines, without necessitating a mathematical model of the system.

Numerous research endeavours have exhibited the efficacy of RL in the domain of wind turbine control. Deljouyi et al. (2021) [161] have proposed two model-free learning algorithms for the purpose of optimizing the power output of wind farms. The authors Wei et al. (2015) [111] introduced an RL approach to optimize the maximum power point tracking control in wind energy conversion systems. In their study, Chen and colleagues (2020) [162] presented a wind turbine controller that is characterized by its robustness. The controller employs adaptive dynamic programming, which is based on reinforcement learning and system state data.

RL has the potential to be applied in the domains of fault diagnosis and predictive

maintenance of wind turbines. The authors Hsu et al [163] have presented a methodology for wind turbine fault diagnosis and predictive maintenance that employs statistical process control and machine learning techniques. The outcomes of the model can furnish technicians with timely alerts, enhance the efficacy of equipment, and diminish the duration of system inactivity during the operation of wind turbines.

To sum up, the utilization of model-free RL has exhibited considerable promise in addressing the difficulties associated with model-based control in wind turbines. Control methodologies based on reinforcement learning have the potential to enhance the precision and effectiveness of wind turbine control, thereby resulting in enhanced operational efficiency and decreased maintenance expenditures.

3.1.2 A Historical Overview and Evolution of Reinforcement Learning: From Markov Decision Processes to Deep Reinforcement Learning

RL is a machine learning paradigm wherein an agent learns to make decisions by receiving rewards and punishments from its environment. The origins of RL can be traced back to the concept of trial-and-error learning in the field of psychology. Edward Thorndike, a psychologist in the early 1900s, developed the Law of Effect. This law posits that actions that result in satisfying outcomes are more likely to be repeated, while actions that result in unpleasant outcomes are less likely to be repeated. This bears a resemblance to the reinforcement learning paradigm’s reward and punishment framework. Edward Thorndike gained prominence for his empirical investigations that involved animals in controlled environments, aimed at comprehending the mechanisms of learning. The "puzzle box" experiments are widely recognized as his most prominent research endeavours.

The experimental procedure involved confining a feline specimen within a container that could only be accessed through the execution of a predetermined behaviour, such as tugging on a cord or activating a lever. Initially, the feline would engage in arbitrary attempts at various actions. Ultimately, the creature would execute the behaviour that initiated the unsealing of the container, thereby enabling its liberation and acquisition of sustenance. Through successive iterations, the feline subject exhibited an enhanced ability to execute the appropriate response for extricating itself from the enclosure. The aforementioned findings indicate that the feline in question was acquiring knowledge through its encounters, strengthening the behaviours that resulted in a favourable consequence (i.e., evading the container and obtaining sustenance) while abstaining from repeating the actions that proved to be ineffective [164, 165, 166].

The origins of RL can be historically situated in the 1950s and 1960s when scholars such as Richard Bellman and Ronald Howard laid the groundwork for the discipline by

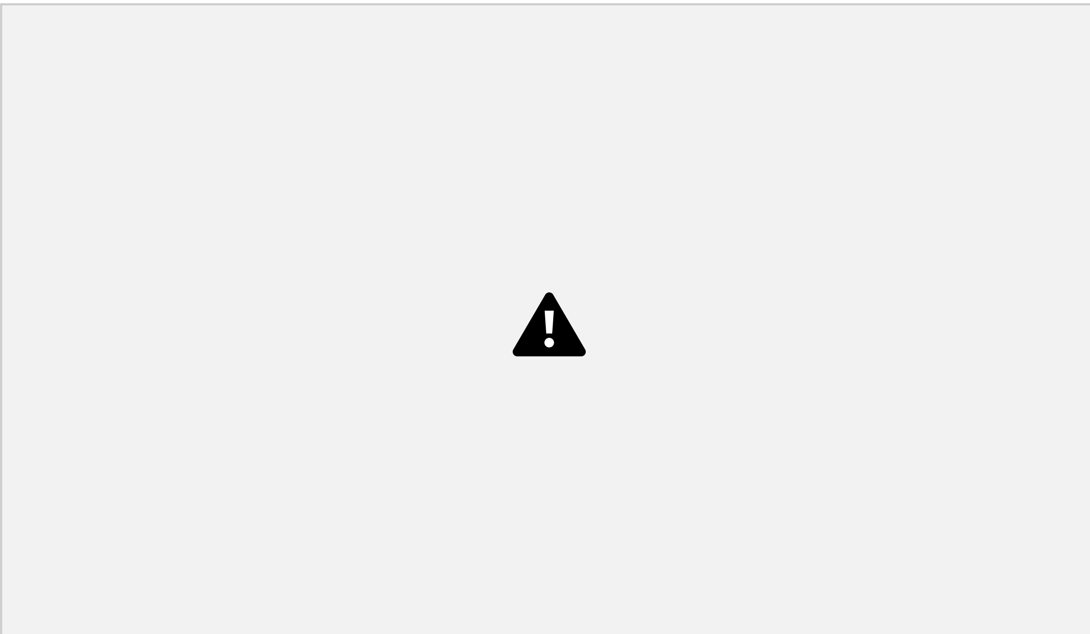

Figure 3.1: Reinforcement learning is biological inspiration

advancing Markov decision theory. R) is intricately linked to MDPs, which serve as mathematical models employed to depict decision-making predicaments wherein the results are partly stochastic and partly under the dominion of the decision maker [167]. RL algorithms are specifically

[171].

formulated to address MDPs through the acquisition of an optimal policy that maximizes the expected cumulative reward over a given time horizon [168].

Richard S. Sutton introduced the *Temporal Difference* (TD) learning algorithm in 1984. The integration of concepts from dynamic programming and Monte Carlo methods in TD learning is a fundamental aspect of reinforcement learning. The contemporary framework for RL, which amalgamates various concepts, was formally established during the 1980s and 1990s. Q-learning, an RL algorithm that has gained widespread usage, was developed by Watkins in 1989. The publication titled "Reinforcement Learning: An Introduction" authored by Richard S. Sutton and Andrew G. Barto, which was initially released in 1998 had a noteworthy impact in unifying the understanding in the domain and is presently regarded as a fundamental text for acquiring knowledge on reinforcement learning [169, 170].

Reinforcement learning involves the agent engaging in interactions with its environment, wherein it receives feedback in the form of either rewards or punishments. The objective of the agent is to acquire a policy that optimizes its total reward throughout a given period. The trade-off between exploration and exploitation is a crucial challenge in the field of RL. The agent is required to maintain a balance between the exploration of new actions and the exploitation of actions that have already been deemed effective

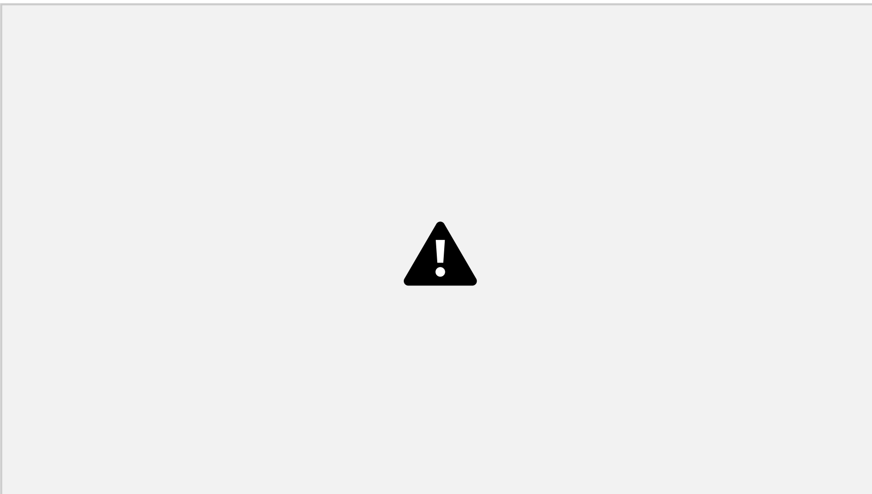

Figure 3.2: Deep reinforcement learning

[171].

RL has undergone a process of evolution, marked by the emergence of DRL as a noteworthy milestone. DRL employs deep neural networks to estimate the value function or policy of the agent, enabling it to acquire sophisticated and abstract representations of the environment, as stated by the source [172]. DRL has been utilized in various domains such as games, robotics, natural language processing, and resource allocation in cellular systems, as evidenced by the works of Fu et al. (2016), Vecoven et al. (2020), and Sun et al. (2020) [173, 174, 175].

To summarize, RL boasts a significant historical background that can be traced back to the 1950s and 1960s. This period saw the inception of MDPs and the establishment of the fundamental principles of the field. The progression of RL has resulted in the emergence of Deep Reinforcement Learning (DRL), which has facilitated the resolution of intricate and conceptual issues. RL is intricately linked to MDPs, and the purpose of RL algorithms is to resolve MDPs by acquiring an optimal policy that maximizes the anticipated cumulative reward over a period.

3.1.3 Taxonomy of deep reinforcement learning

The classification system for deep reinforcement learning comprises two primary divisions, namely model-based and model-free deep reinforcement learning. Deep reinforcement learning algorithms that are model-free acquire knowledge through experience, without explicitly constructing a model of the environment's dynamics. In contrast, deep reinforcement learning algorithms that are model-based aim to construct a clear model of the dynamics of the environment in order to minimize the requirement for environment samples [176].

Recent advancements in deep learning have facilitated the success of

model-free

deep reinforcement learning algorithms in an increasing number of tasks [177]. The algorithms in question encompass DQN, policy gradient methods, and actor-critic methods. The DQN algorithm is a type of model-free approach that employs a deep neural network to estimate the action-value function. Policy gradient techniques involve the direct optimization of the policy function through gradient ascent. Examples of such methods include A3C (*Asynchronous Advantage Actor-Critic*), ACKTR (*Actor Critic using Kronecker-Factored Trust Region*), PPO (*Proximal Policy Optimization*), and TRPO (*Trust Region Policy Optimization*). Actor-critic techniques amalgamate the benefits of policy gradient and value-based approaches, such as DDPG and SAC (*Soft Actor-Critic*). Value-based model-free deep reinforcement learning algorithms, including DQN, DDQN (Double Deep Q-Network), Dueling DQN, and DRQN (*Deep Recurrent Q-Network*), have been developed and studied in recent years (Lazaridis and Karakostas, 2020; Sewak and Sharma, 2019) [178, 99].

Dyna and *Monte Carlo Tree Search* (MCTS) are among the model-based deep reinforcement learning algorithms. The Dyna algorithm is predicated upon a model based approach, wherein a learned model is utilized to simulate the environment and subsequently update the value function. The MCTS is an algorithmic approach for tree search that leverages a trained model to simulate the environment and explore the optimal course of action. The ME-TRPO algorithm is a model-based approach that leverages an ensemble of models to enhance the stability of the learning process. This has been demonstrated in various studies, including those by Kurutach et al. (2018), Plaat et al. (2020), and Lazaridis et al. (2020), among others [177, 176, 178].

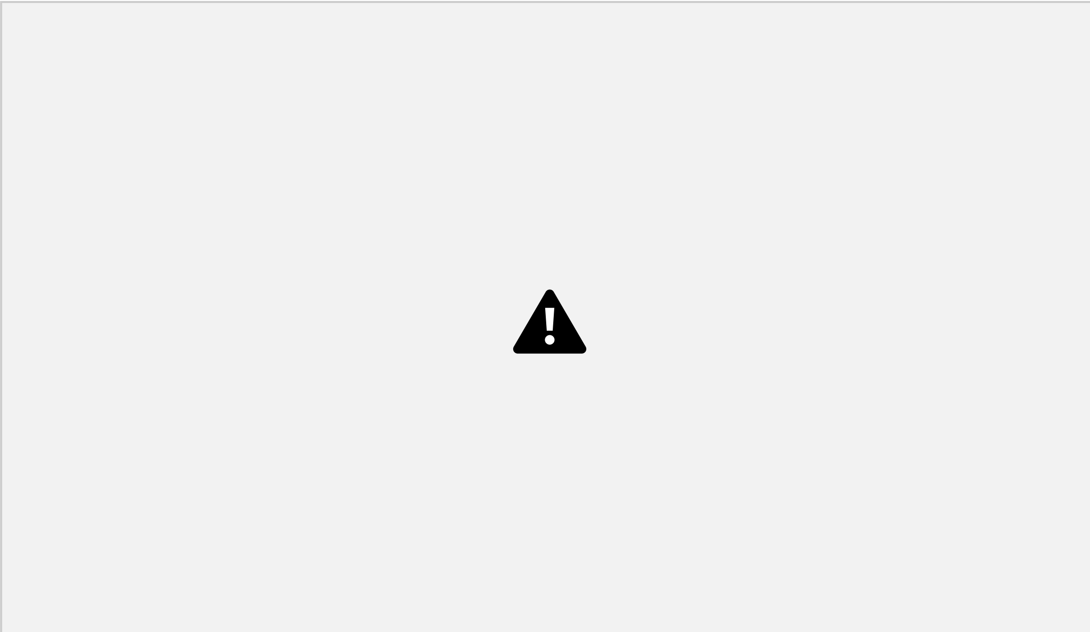

Figure 3.3: Deep reinforcement learning taxonomy

The *Imagination-Augmented Agents* (I2As) is an innovative deep reinforcement learning architecture that integrates both model-free and model-based elements, as described in Weber et al.'s work (2017) [179]. Ren et al. (2018) [180] proposed DeepPath, a deep reinforcement learning model that integrates embedding and path based approaches to address the learning-to-reason problem.

The field of deep reinforcement learning can be classified into two main categories: model-based and model-free methodologies. Algorithms that are model-free acquire knowledge through direct experience, without the need to construct an explicit representation of the dynamics of the environment. In contrast, model-based algorithms generate a clear representation of the dynamics of the environment in order to minimize the requirement for environmental samples. Hybrid methodologies that integrate both model-based and model-free components have also been proposed in the literature [179, 180].

3.1.4 Model-free deep reinforcement learning algorithm

RL algorithms that are model-free have been found to be an extension of optimal control techniques. DQN is a well-known value-based approach that is limited to discrete environments. On the contrary, policy-based approaches frequently converge at a limited optimum. The actor-critic approach is a hybrid of policy-based and value based methods that effectively handles continuous domains. The DDPG algorithm is a noteworthy illustration of an actor-critic approach.

The DDPG algorithm represents a logical advancement from the DQN approach. DQN was found to be inadequate in addressing continuous environmental problems, largely due to the curse of dimensionality. In order to address this concern, the fundamental equation of deep Q-learning was modified to prioritize the Q-learning policy that employs the *argmax* of Q. The utilization of a neural network critic in the actor-critic architecture has enabled the implementation of reinforcement learning in continuous environments. The actor-network employed state-action data to estimate the optimal subsequent action and updated the network weights through the use of gradient descent. The critic network provided an evaluation of the action produced by the actor network, providing input on the efficacy of the action in optimizing the agent's total reward. DDPG incorporates two crucial concepts from DQN, namely the utilization of replay buffer and target networks.

The replay buffer, commonly referred to as experience replay, is a repository of state, reward, and action transitions utilized in the training process. The target network serves the purpose of enhancing the stability of the training process by reducing the frequency of weight updates in comparison to the primary actor-critic networks. This approach effectively mitigates the risk of overfitting. The utilization of the Ornstein-Uhlenbeck process for noise modelling is a significant divergence within the actor network. This

particular procedure aids in the resolution of the inherent exploration-exploitation dilemma present in certain problem domains. The present study refrains from exploring the intricate details of said processes, in order to maintain the relevance of the content for a wider readership [181], [182], [95].

3.1.5 Twin delayed deep deterministic policy gradient (TD3)

The DDPG algorithm has established a specialized area of application in addressing obstacles encountered in continuous environments. However, the model has certain limitations, as it displays vulnerability during the training stage and its ultimate performance is significantly influenced by the initialization process. The emergence of the TD3 algorithm has been proposed as a potential solution to address the aforementioned limitations, as it represents an advanced variant of the DDPG algorithm. TD3's improved performance can be attributed to three primary modifications made to the DDPG algorithm:

- Delayed policy updates: TD3 relies on a fundamental principle of infrequent updates to the target network, which distinguishes it from DDPG. By means of a training regimen that is relatively limited in scope, the agent acquires progressively higher rewards as time passes, resulting in an ultimate enhancement of its overall performance.

- Double Q-learning with Clipping: TD3 algorithm has been designed to mitigate the issue of overestimation of action values in DDPG. This is achieved through the incorporation of two target Q-learning networks. Although the implementation of dual Q-learning networks alone does not result in significant enhancements, it should be noted that when both networks are linked to a common replay buffer and actor-generated policy, opting for the minimum action-value prediction can overcome this limitation. The method proficiently curbs any undue overestimation of action values.

- Target policy smoothing: The proposed modification involves the incorporation of stochastic perturbations prior to the estimation of action values, thereby resulting in the attenuation of local maxima. The introduction of noise is found to be beneficial in enhancing the efficacy and stability of the algorithm.

By incorporating the aforementioned three enhancements, the TD3 algorithm demonstrates superior efficacy and proficiency in addressing continuous environments relative to its predecessor, DDPG [182], [95], [181].

3.1.6 Reinforcement learning applications

Reinforcement learning has demonstrated efficacy across a range of domains, including but not limited to robotics, finance, power systems, computer vision, and education. Reinforcement learning has been applied in various applications within the realm of robotics, including but not limited to motion control, self-driving, and personalized robot-assisted dressing, as evidenced by the works of Fu et al. (2019) [183] and Zhang et al. (2017) [184]. Reinforcement learning has been utilized in the field of finance for the purposes of predicting stock values and implementing deep hedging strategies for derivatives, as noted by Liu et al. (2022) [185]. Reinforcement learning has been applied in power systems for various purposes such as demand response management, operation control, and economic dispatch, as evidenced by the works of Chen et al. (2022) [186] and Li et al. (2020) [187]. Reinforcement learning has exhibited noteworthy achievements in diverse domains within the field of computer vision, as evidenced by prior research [188]. The utilization of reinforcement learning has been observed in the field of education as a means of imparting problem-solving skills, as evidenced by Forgan and his colleagues in their work [189].

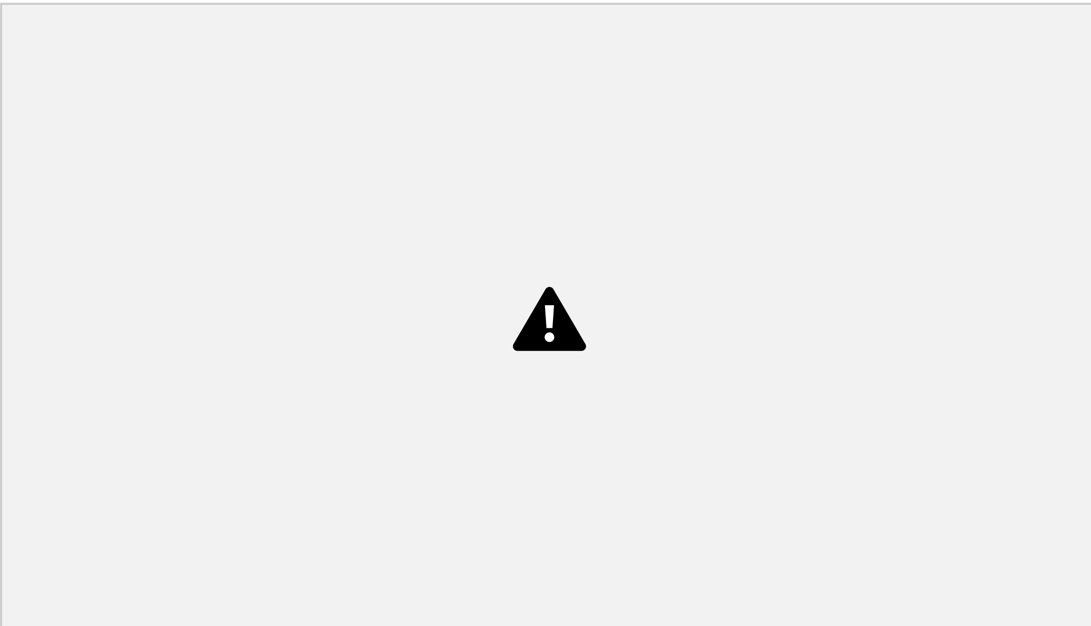

Figure 3.4: Deep reinforcement learning applications in different fields

The implementation of reinforcement learning has proven to be efficacious in various domains, including the development of a controller for sustained inverted flight on an autonomous helicopter, as evidenced by Zhang et al.'s (2017) [184] research. An additional instance pertains to acquiring proficiency in the sport of Keepaway soccer [185]. The utilization of reinforcement learning has been observed in the context of directing an independent taxi, as evidenced by Han et al.'s study on routing

[190]. Furthermore, the utilization of reinforcement learning has been observed in the amalgamated development of tiltrotor arrangements and their practical implementations [191].

The aptness of reinforcement learning in these domains is attributable to its capacity to acquire knowledge from past encounters and enhance actions by leveraging rewards. Reinforcement learning algorithms exhibit the ability to dynamically adjust to varying environmental conditions and acquire knowledge through iterative experimentation. Reinforcement learning has the potential to facilitate the execution of intricate tasks and the adjustment to varying circumstances in the field of robotics. Reinforcement learning has been employed in the field of finance to forecast stock prices and enhance investment tactics. Reinforcement learning has the potential to enhance energy efficiency and cost-effectiveness in power systems. Reinforcement learning has been shown to enhance object recognition and image classification in the field of computer vision. Reinforcement learning has the potential to enhance problem-solving abilities and facilitate personalized learning experiences within the realm of education.

In closing, reinforcement learning has exhibited significant promise across diverse domains and has been effectively implemented in numerous practical scenarios. The capacity to acquire knowledge from experience and optimize actions based on rewards renders it a viable strategy for resolving decision-making challenges in intricate and ever-changing settings.

3.2 Deep Reinforcement Learning with TD3 for Advanced Control of PMSG-based Wind Turbines

This thesis introduces a novel approach to controlling variable-speed wind turbines that utilizes a TD3 agent as a data-driven solution. Specifically, the focus is on PMSG based turbines. The predominant body of literature centres on the application of RL to replace the present control loop in PMSMs, while preserving Proportional-Integral (PI) controllers for speed regulation. To the best of our knowledge, this research constitutes a groundbreaking endeavour in utilizing DRL as the sole method for single-loop control in these applications. This approach stands in stark contrast to previous studies that relied on cascaded control loops, such as the adaptive PI with a wavelet neural network (WNN) proposed in the work by Alizadeh et al. (2015) [192]. Previous studies on wind turbines have predominantly concentrated on utilizing DRL to detect the most efficient *Maximum Power Points* (MPPs) or to assist other controllers in acquiring knowledge about the internal gain parameters of diverse control algorithms. By contrast, the proposal put forth presents a comprehensive control solution for variable-speed wind turbines utilizing DRL. The efficacy of the algorithm in effectively managing the

system is demonstrated, even in scenarios where aerodynamic torque information is not available.

In light of the inherent connections between reinforcement learning algorithms and optimal control methodologies, we compare the efficacy of our suggested approach with that of the LQR. The results of our study suggest that the RL agent exhibits superior performance compared to the LQR, while maintaining a similar level of control effort. Furthermore, the RL agent exhibits enhanced robustness towards parameter fluctuations in comparison to the LQR. In order to achieve a well-rounded evaluation, the LQR controller was provided with knowledge pertaining to parameter fluctuations in situations marked by parameter ambiguities.

The present investigation utilized TD3, a sophisticated model-independent DRL algorithm that constitutes a progression of the DDPG algorithm. The results of our study provide support for the notion that utilizing DRL as the predominant method of control shows significant potential for PMSG systems and wind turbines with variable speeds.

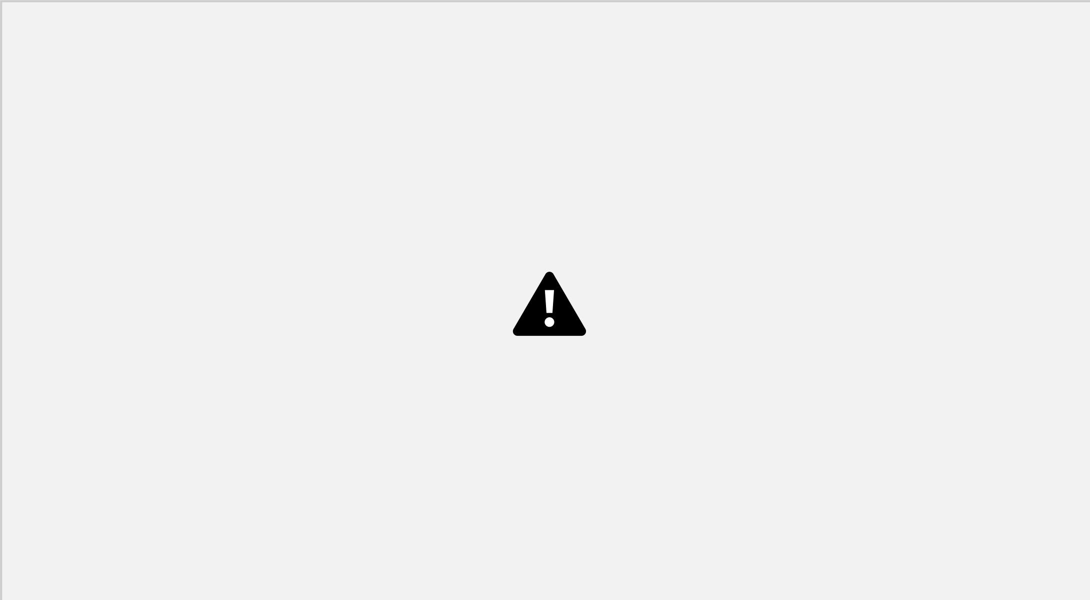

Figure 3.5: Comprehensive wind turbine control block diagram with DRL, where θ denotes the rotor angle as measured by the encoder.

The main contributions of this thesis can be summarized as follows:

1. The utilization of DRL, particularly the TD3 algorithm, has been introduced to tackle the challenges associated with MPPT in WECS. This approach is noteworthy as it has not been previously documented, particularly in relation to PMSGs.