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ADAMA II WIND FARM LONG-TERM POWER GENERATION FORECASTING BASED ON MACHINE LEARNING MODELS

BY

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A thesis submitted to the center of Renewable Energy Technology School of Graduate Studies of Addis Ababa Institute of Technology in partial fulfillment of the requirements of the Degree of Master of Science in Energy Technology

ADVISOR

MESFIN BELAYNEH AGEZE (PhD)

AUGUST, 2022

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DECLARATION

I certify that this research work titled "ADAMA II Wind Farm Long-Term Power Generation Forecasting Based on Machine Learning Models" is my work. The work has not been presented elsewhere for assessment. Where material hasn't been used from other sources, it has been properly acknowledged.

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ACKNOWLEDGEMENTS

Primarily, I would like to give glory to Almighty God and the Virgin Mary without which the completion of this thesis would have been unthinkable.

The success and outcome of this thesis required guidance and assistance from an advisor. I am extremely privileged to have got this all along with the completion of my thesis. All that I have done is only due to such supervision and assistance and I would not forget to thank Dr. Mesfine, for providing me an opportunity to do the thesis work in the forecasting wind power generation based on machine learning giving me all support and guidance which made me complete the thesis duly.

Finally, I would like to thank my family, my friends, and my classmate who always stood by my side

ABSTRACT

Currently, renewable energy production from wind farms with hundreds of megawatts connected to the grid is increasing. Wind energy is intermittent and random due to being highly dependent on wind speed nature, hence grid interconnection among nations of the Eastern Africa region plans face reliability issues. Accordingly, Ethiopian Electric Power needs to diligently plan ahead of time the allocation of generating units in its power plants to match its national and regional energy demand (MW) because if the demand is higher than the generation it can cause several blackouts resulting in a huge loss to the economy; on the other hand, if the generation is higher than the demand the extra electricity will be wasted and it can also create an unnecessary load on the transmission lines.

This thesis studies the power production performance analysis of the Adama II wind farm using MATLAB SIMULINK with scenarios of fault ride-through capability, short circuit fault, control fault, and wind speed variation impact. Furthermore, conducting long-term wind power forecasting to safely national and regional grid integration by applying basic time series models SARIMA and then extended to linear regression, random forests, and XGBoost to accurately forecast the Power output of the wind turbine.

Impact and performance analysis result has observed a short circuit and control fault on the grid interconnection point occur will bring a grid disturbance to the power system. But a rapid speed variation will be composited by the farm's reactive power supply. Moreover, Adama II wind farm delivery 0MW upto 153MW power to gird, during maintenance and some grid and turbine faults it failed to delivery as its capacity. Main reason to downtime is due to grid fault, night time due to light load at night Adama II wind farm don't have voltage regulator to cop up its power fluctuation. Furthermore, the thesis developed a one-year ahead forecasting model to improve the Adama II wind power plant grid integration impact for reliable plant operation and maintenance schedule. The study tests 1 hour, 1 week, and 12 months. 1-hour ahead and 1-week ahead forecasting using SARIMAX, Elastic net, and Random Forest regression give around 90% R^2 score and 2~4% MAPE using lag variables for short-term 1-hour ahead and 1-week ahead forecasts. But for more than 1 month ahead forecasting XGBoost (with Fourier terms for seasonality) performs very well for longer forecast windows.

Key Words: Variable Renewable Energy, Wind Farm, Performance, Long-Term Forecasting, grid integration.

List of Abbreviations and Acronyms

AEP:	Annual Energy Production	MVA:	Mega Volt Ampere
ANN:	Artificial Nural Network	MW:	Megawatt
ARIMA:	Autoregressive Integrated Moving Average	PCC:	Point of Common Coupling
DFIG:	Doubly Fed Induction Generator	PMG:	Permanent Magnet Generator
EEP:	Ethiopian Electric Power	PV:	Photovoltaic
ETAP:	Electrical Transient and Analysis Program	PWM:	Pulse Width Modulation
FACTS:	Flexible Alternating Current Transmission System	RPP:	Renewable Power Plant
GSC:	Grid side controller	RSC:	Rotor Side Controller
GTP:	Growth and Transformation Plan	RMSE:	Root Mean Square deviation
HVDC:	High Voltage Direct Current	SCADA:	Supervisory Control and Data Acquisition
IGBT:	Insulated-gate Bipolar Transistor	SVM:	Support Vector Machine
KNN:	K Nearest Neighbors	THD:	Total Harmonic Distortion
KV:	Kilo Volt	VRE:	Variable Renewable Energy
LSTM:	Long-short time memory	VMD:	Variational Decomposition Mode
MAE:	Mean Absolute Error	WF:	Wind Farm
MAPE:	Mean Absolute Percentage Error	Xgboost:	Extreme Gradient Boosting

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CHAPTER 1 INTRODUCTION

1.1 Background

Renewable energy technologies are becoming very cost-effective and, thus increasingly attractive to meet global energy demand for grid electrification in locations where renewable resources are available.[1].

Nowadays Ethiopia's economy and population are getting increased exponentially analogs to this the energy demand is in need to meet. Ethiopia can generate over 60 gigawatts of electric power from solar, geothermal, hydroelectric, and wind sources. Currently, almost 90% of the energy demand of the country is covered by hydroelectric power, while the remaining 8% is wind power and 2% is from thermal sources. [2]

As the Ethiopian grid system is dominated by hydropower and has been affected by drought, hence the plant would run below their capacity unexpectedly. This is challenging the country to reliable supply energy to both national and regional interconnected networks. To resolve such reliability issues. The sole electric power producer Ethiopian Electric Power is now diversifying and the increasing energy mix ratio with other renewable energy sources of solar, geothermal, and wind. This renewable energy source penetration of the grid system will result in a more climate-resilient power system[3].

Along with the work that is continuing on the Grand Ethiopian Renaissance Dam on the Nile River Ethiopia aims to boost other green power projects, harnessing geothermal, solar, and wind energy. To meet the energy mix in need, one of the promising renewable energy sources of Ethiopia is wind energy. Moreover, there is a favorable condition to construct a large-scale wind farm. As wind power is renewable clean energy with short construction periods. Thus, Ethiopian Electric Power (EEP) has planned to develop wind power plants to resolve the shortage of electric power supply. This will result in increased penetration of wind energy into EEP's grid.

Till now Ethiopia has explored a small portion of wind resources Ashegoda (120MW), Adama I(51MW) & II (153MW). Furthermore, it's expected to persist increase in the coming years as Assela(100MW) and Aysha II (120MW) are under construction and many more are planned to implement[4].

However, the intermittency and uncertainty of wind speed make it a challenge to integrate wind power into the grid system. Meanwhile, to optimize the demanding schedule, the precise electricity requirements and the usage load curve pattern of the customers is necessary. This is the important task where the energy prediction requirement arises into play. A time-series wind power production forecasting would insist on resolving grid integration-related issues. This thesis discuses machine learning long-term power production forecasting of the Adama II wind farm and evaluate grid integration performance for sustainable national and regional power supply systems.

1.2 Problem Statement

Nowadays, wind farm construction cost has fallen relatively to hydroelectric power plants[5], [6]. Furthermore, for the Ethiopian government's energy mix policy to sustain energy supply, wind power plant development is expected to grow significantly in the coming years. However, wind energy is intermittent and random due to being highly dependent on wind speed nature, hence grid interconnection among nations of the Eastern Africa region plans face reliability issues. Ethiopian Electric Power needs to diligently plan ahead of time the allocation of generating units in its power plants to match its national and regional energy demand (MW) because if the demand is higher than the generation it can cause several blackouts resulting in a huge loss to the economy; on the other hand, if the generation is higher than the demand the extra electricity will be wasted and it can also create an unnecessary load on the transmission lines.

Adama II wind farm penetration on-grid system facing a reliability issue, speed variation affects turbine and farm performance, power quality due to lack of voltage regulator at the farm, and system security from system operation and system planning aspects. To accommodate Adama II wind farm penetration to Ethiopia's power grid system for stable operation and safety of the grid system, it is critical to successfully predict wind energy generation. This thesis aims to investigate the power generation performance and develop a wind power generation forecasting model with a long-term horizon based on a machine learning algorithm as a case study of the Adama ll wind farm.

1.3 Objective

1.3.1 General Objectives

The main objective of this study is to investigate the power production performance and grid integration of the Adam II wind farm and develop long-term power production forecasting based on a machine learning-based model

1.3.2 Specific Objectives

- To analyze Adama II wind farm power production performance and grid interactions
- To identify and examine suitable mitigation methods for wind farm power variability and uncertainties
- To develop a long-term wind farm power production forecasting model;
- To validate the developed forecasting model and simulate Adama II wind farm's future production

1.4 Scope of The Thesis

This study discussed Adama II wind farm grid integration performance for sustainable national and regional power supply systems and machine leaning based long-term power generation forecasting of Adama II wind farm

1.5 Research Questions

The study sought to address the following specific questions

- How do the intermittency and uncertainty of wind speed affect the grid integration performance of the Adama II wind farm?
- When is the maintenance of the Adama II wind plant to be held without affecting grid stability?
- How to forecast one-year head Adama II wind farm power production performance with the least error?
- How seasonal climate variation affects Adama II wind power production?

1.6 Significance of The Thesis

Ethiopian Electric Power needs to diligently plan ahead of time the allocation of generating units in its power plants to match its national and regional energy demand (MW). Because if the demand is higher than the generation it can cause several blackouts resulting in a huge loss to the economy; on the other hand, if the generation is higher than the demand the extra electricity will be wasted and it can also create an unnecessary load on the transmission lines. Hence, it is very important to have a forecast of energy production to be able to allocate appropriate resources to meet its demand. A year, month, or day-ahead forecast can help the utilities plan for a larger time scale but for smoother daily operations an hourly (or even better) forecast can prove very useful.

This study will involve analyzing the past 6 years of hourly power production data of Adama II wind farm to find trends in power production around an hour of the day, day of the week, the season of the year, etc., and also to check if factors like wind speed, wind direction and outdoor temperature in the wind farm which affect the power production. That is, a model can be built to predict power production given parameters like the day of the week, time of the day, and season.

The developed prediction model can be utilized by Ethiopian Electric Power (EEP) to effectively plan their power generation operations and balance the demand with appropriate supply. An efficient forecast can prove very useful for planning day-to-day operations, properly meeting' energy demand, and avoiding the excess generation of energy.

1.7 Structure of The Thesis

The thesis contains five chapters, Chapter one presented a brief introduction to wind farm grid integration and its challenge. Followed by Chapter two discussed literature related to wind farm grid integration and power production forecasting with different approaches. And Chapter three discussed a methodology to meet the seated thesis objectives that investigate the power generation performance Adama II wind farm and long-term forecasting. Chapter four and Chapter five discussed the results and discussion for Adama II wind power generation performance and present results of long-term forecasting models. Finally, study comes to Chapter 6 Conclusion and Recommendations respectively comprise sate a conclusion of the thesis come through and present some recommendations for further study and implementation.

CHAPTER 2 LITERATURE REVIEW

2.1 Background

World renewable energy demand is becoming increasing rapidly as urbanization and economic development have been boosted[7]. According to a global energy review report on renewable electric power generation, 2021 has registered the fastest year-on-year growth since the 1970s, as it increases by more than 8% to reach 8,300 TWh, [8]. Next to hydroelectric power wind power generation is the largest renewable energy source around the globe. More than 6% of global electricity in 2020 with 743 GW of global capacity is from wind [9].

As Ethiopia's economy grows fast, the energy demand is enormously increasing. Thus, Ethiopia is dealing with renewable energy sources[10]. Ethiopia's energy sources more than 90% depend on hydro, but Ethiopia formulating a growth and transformation plan (GTP) to explore wind, geothermal, solar as well as biomass[11]. Recently wind energy is significantly contributing to diversifying the Ethiopian energy mix by taking a considerable share from hydro. Till now Ethiopia has explored a small portion of wind resources Ashegoda, Adama I(50MW) & II (153MW). It's expected to persist increase in the coming years as Assela(100MW) and Aysha II (120MW) are under construction and many more are planned to construct [12]. However, as the development of wind energy becomes increasing[13]. it possesses challenges and technical issues related to grid integration due to the uncertain and intermittent nature of seasonal climatology factors [14], [15]. The main issues related to wind farm integration in power grid systems are power system transients and harmonics, voltage and frequency variations, low power factor (high reactive power), electromagnetic interference, and synchronization [16].

Considering the development of large-scale wind farms will improve the effort to meet Ethiopia's electricity demand in the future[17]. Hence, the wind power forecasting model is an effective method for reducing the adverse impact of wind farms on the power grid and for increasing the penetration of wind power in the grid system[18]. Moreover, forecasting provides technical support for the safety, stability, and economic maintenance and operation of wind farms. However, wind power forecasting is uncertain owing to a combination of wind speed uncertainty and variations in wind farm performance[19].

2.2 The Architecture of a Modern Wind Turbine and Wind Farm

Wind turbines convert the movement of wind into electrical energy using a rotating turbine and a generator. Nowadays, wind power is growing rapidly and supplying significant shares of energy in large regions[9]. Wind energy plants are presently being moved toward a 5MW single WTG power generation capacity and a few GW wind farms.

Wind technology after commercialization it is passing through a lot of improvement and development, however, the design of fundamental architecture had very little changed relatively very little. Which is almost all wind turbines have upwind rotors and yawed aligned to wind direction.

The three-bladed wind turbine has moderate acceleration and a separate front bearing, with a low-speed shaft connected to a gearbox. Such characteristics of the three-blade rotor are suitable for the most popular four-pole (or two-pole) generators. Most large wind turbines' pitch could vary continuously, under active control to regulate power at maximum operational wind speeds.

There are different support structures namely, tubular steel towers, concrete towers, concrete bases with steel upper sections, and lattice towers with various tower heights concerning site-specific and turbines[20]. A typical wind farm layout is shown below in Figure 2.0.1

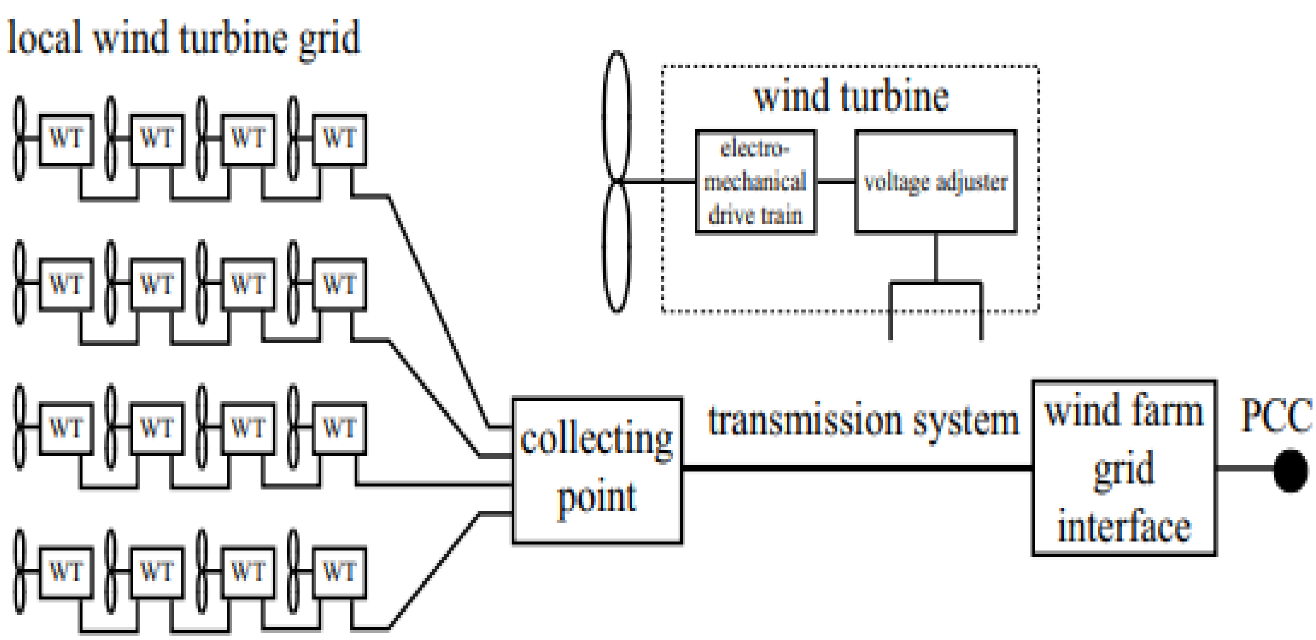


Figure 2.0.1: Typical Wind farm layout [19]

Conventional architecture of multi-stage gearbox and high-speed generator which is generator shaft drive connected directly to the rotor drive through a gearbox. This architecture rotor technology is one of the leading commercial designs and the upwind three-bladed rotor. However, unconventional trends in nacelle architecture are becoming an issue. To resolve such issues direct-drive systems of Enercon, and many direct-drive designs based on permanent magnet generator technology have appeared in recent years[21]. Furthermore, several hybrid systems, such as Multibird, which employ one or two gearing stages, and multi-pole generators, have also emerged. This different architectural configuration is to meet the ultimate goal of minimized capital cost and maximum reliability[22].

2.3 Existing Findings of Wind Farm Gird Integration Challenges

The integration of wind power in the power system is now an issue to optimize the utilization of the resource and the high rate of installation of wind generating capacity, which is necessary to achieve sustainability and security of supply[19]. With the increasing share of wind energy in the global power market, a large amount of wind power is integrated into existing grids. Thus, the expected growth in wind power could soon exceed the current capability of grids with today's technology. To prepare for situations in advance, the influence of intermittent wind power on stability and system security must be properly addressed. The impacts of wind power on a power grid depend on the level of wind power penetration, grid size, and generation mix of electricity in the grid. Undoubtedly, there is no problem with low wind power penetration in a large power grid. However, integrating large utility-scale wind power presents unique challenges[24].

The current key concern about renewable energy is the technologies used to harness the energy from nature and appropriate transmission technologies to bring bulk renewable energy to load centers. wind energy has developed in the form of doubly-fed and permanent magnet synchronous machines. The deficits in the majority of renewable energy technologies are the inability to provide reactive power support and no possibility of immediate energy balance due to lack of inertia. However, this problem can be rectified by utilizing technology as a combination of asynchronous and synchronous machines and inverters, along with other technologies such as FACTS devices with innovative controls. Several operational security concerns and associated risks can also be minimized by using suitable technologies and control strategies. Other non-technical risks, however, can be handled by various entities involved in the renewable energy business as they have tools to mitigate and transfer the risks. as wind penetration increases, future technical requirements may well become more onerous. One possible requirement is for an 'inertia function'. The spinning inertia of a conventional power plant provides considerable benefit to the power system by acting as a flywheel thereby reducing the short-term effects of differences in supply and demand. Variable-speed turbines have no such equivalent effect, but theoretically, their control systems could provide a function that mimics the inertia effect.

2.4 Background About ADAMA II Wind Farm and Existing Challenges

ADAMA II wind farm is located in the middle of Ethiopia, about 7km west of Nazret, and 3.5km west of Adama I wind farm, with an altitude elevation of 1741~2200m. The central geographical position of the wind power farm is 39°13'6.46" E, 8°34'48.12" N, stretching from northeast to southwest as shown below in Figure 2.0.2. The total installed capacity of the Adama II Wind power project is 153MW with 102 units of 1500kW wind turbines [21]. Analysis of the dynamic voltage stability of Adama II wind farm penetration into the existing Ethiopian grid using PSS/E 33 simulation software[25]. investigate the dynamic response of Adama II wind farms integrated into the grid using the aggregated model of grid-connected wind farms using MATLAB/Simulink tool and ETAP software [27]. Compare the actual energy performance and the feasibility study. Furthermore, investigates prevailing and secondary wind directions obtained were ENE and NE with 35.7% and 19.1% while, in the feasibility study, ENE with 36.5% and E with 17.3%. From the SCADA data, the Capacity factor, Annual Energy Production (AEP), and Availability of wind turbines were determined as 30.5%, 398 GWh, and 95.1%[28]. Repositioning WTGs to investigate potential areas will improve a net AEP from 403.669 GWh to 478.786 GWh, hence the Net Annual Energy Production, increment of about 18.6 % [27], [29].

Generally, Adama II wind power penetration into Ethiopian grid issues are below listed [25]:

i. Voltage stability is the principal issue that will influence the operation and security of the Adama II wind farm and power network since voltage stability deterioration is mainly due to the large measure of reactive power consumed by the WTs during their continuous operation and system contingencies.

ii. Adama II wind farm could cause genuine voltage stability issues because of its output variability and discontinuity.

iii. Moreover, wind turbines have possessed the limited capability to inject reactive power into the point of a common couple (PCC) to support the voltage during short-circuit. The goal of this study is to examine the grid integration performance of the Adama II wind farm at different wind speed variations using the MATLAB SIMULINK model.

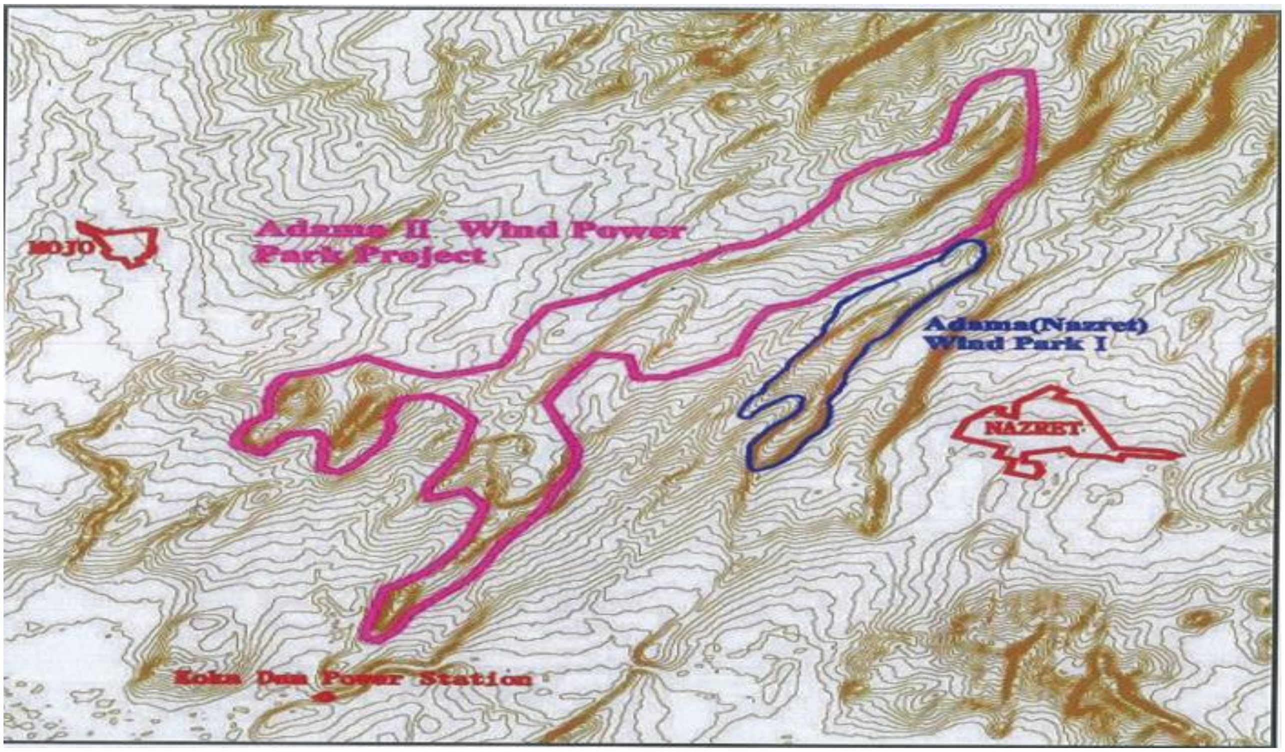
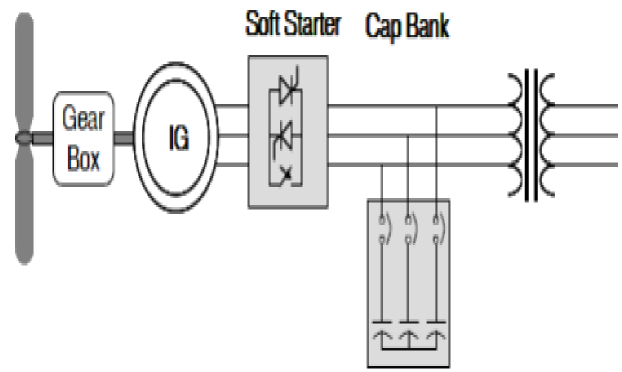
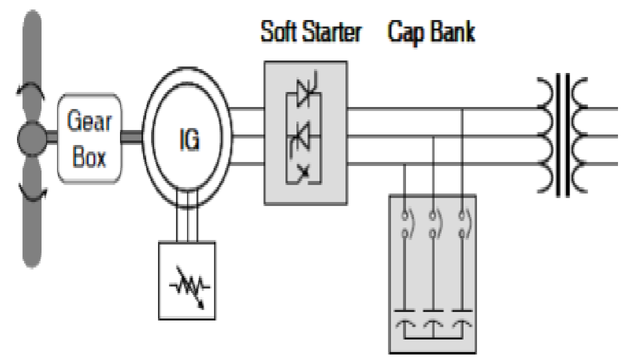


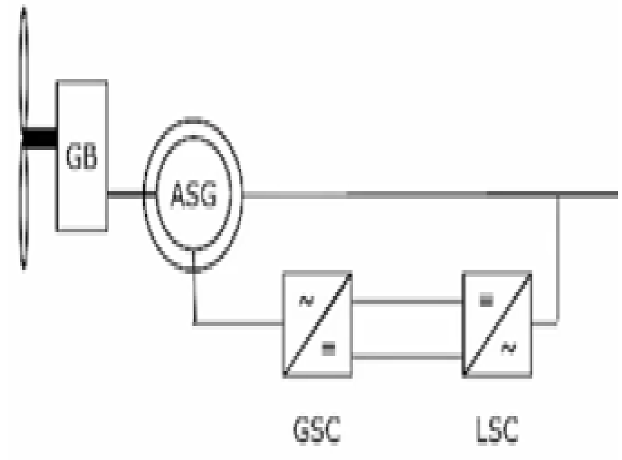
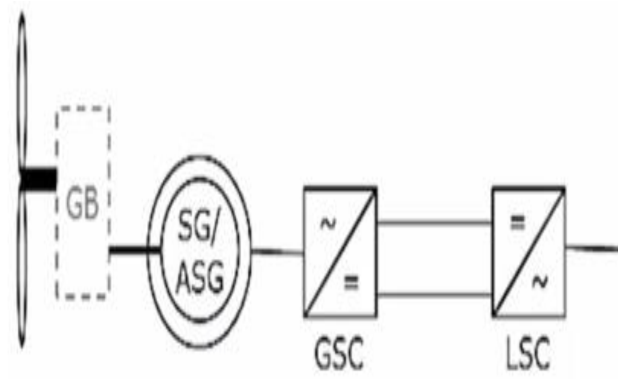
Figure 2.0.2: Adama II Wind Farm Location[30]

2.5 Wind Turbine Performance at Different Configurations

Wind turbine generator (WTG) technology development has advanced from Type 1 and 2 induction-based generators to Type 3 doubly-fed induction generators and Type 4 full-power, conversion-based generators, Because Type 1 and 2 generators consumed reactive power from the grid, they were not “grid-friendly,” and they are no longer utilized in utility-scale turbines. By contrast, Type 3 and 4 WTGs are grid-amicable and can consume or generate reactive power to support grid functions see details in see Table 2.0.1. These turbines give active and reactive power control, low-voltage ride-through (LVRT), and other features that could expand the security and reliability of the grid[31].

Table 2.0.1:Wind turbine configuration [32]

Wind turbine type	**Operation principle**	**Merit**	**Drawback**	**Schematic diagram**	**Ref.**
Types 1	-Squirrel-Cage Induction Generator coupled through a gearbox to the turbine and attached directly to the stepped-up transformer. Use also a back-to-back converter.	-Simple and low cost -Rugged, low maintenance -Rapid transient response -No current harmonics	-Poor voltage control ability -Large starting inrush, required capacitor, and staggered starts -Difficult to control per schedule -Low efficiency		[22]
Types 2	-Wound rotor induction generators connected a variable resistor in the rotor circuit via slip ring to control speed and torque.	-Handle the rotor currents quite quickly into deep consistent power in any event, during blasting circumstances, -High starting torque	-Poor zero-voltage ride-through capability -Very limited speed control -Low efficiency -Poor active and reactive control ability -limited speed ranges		[33]

Types 3	- Doubly Fed Induction Generator the utilization of an electronic AC-DC-AC power converter connected between the wound rotor and the grid permits control of the magnitude and frequency of the rotor current	-Good conversion efficiency -Decoupled control of active/reactive power Capable of ancillary service (voltage/frequency regulation) support	-Limited fault ride-through and voltage regulation capability -Large short circuit contribution -Required compensation devices. -The crowbar circuit limits system support during contingencies		[34]
Types 4	-Rotor drives gearbox in geared systems to increase generator shaft speed -Generator converts mechanical power to AC electric power, generators can be asynchronous, permanent magnet, or synchronous	-Maximum flexibility fully controllable converter interface -Controllable short circuit contribution -Theoretically infinite duration low voltage ride-through capability	-Limited (but controllable) fault current contribution may require sophisticated collector protection		.[22]

2.6 Grid Integration Requirements for Renewable Energy

Due to environmental concerns, government policies and decreasing cost of technologies renewable energy development has been exponentially growing. However, as the penetration of renewable power sources increases, new challenges in system planning and operation are becoming evident. There are short-term operational challenges as well as long-term planning challenges due to the intermittent nature of renewable power generation primarily from wind and solar photovoltaics[35].

To accommodate these new technologies, the grid must be evolved and operated in such a way that it ensures the maximum accommodation of renewable power generation is utilized efficiently and economically. Renewable energy grid integration considers several factors. Such as:

- The optimum coordination of balancing resources in the grid.
- Appropriate government and utility regulations to ensure minimum requirements of grid-connected systems are met.
- Smart grid technologies to coordinate renewable generation and ancillary services.

Usually, a grid code establishes rules for wind power connection to the power system. The higher level of penetration results in the need for advanced wind power capabilities, stronger regulation support, and better storage facilities required from the grid. However, even in countries that have not yet developed a grid code, new VRE generation facilities still need to comply with a basic set of technical standards and the rules of interconnection to ensure reliable operations both of a VRE as an individual plant, and a grid as an interconnection of multiple energy resources with new VRE.

Table 2.0.2 Wind turbine considerations for Technical Specification[33][36]

Generator Type	Voltage Control Capabilities	Reactive Power Capabilities	Grid Short Circuit Response	Fault Ride-Through Capability
Type I	Use power factor correction capacitors (PFCCs) to keep up with the power factor or reactive power output on the low voltage terminals of the machine to a setpoint	Use PFCCs to keep up with the power factor or reactive power of the machine to a predefined set point.	Can be addressed as a voltage source in series with the direct axis sub-transient inductance.	During the fault, the external resistance control was to result in short-circuiting of the generator rotor
Type II	Use power factor correction capacitors (PFCCs) to keep up with the power factor or reactive power output on the low voltage terminals of the machine to a setpoint	Use PFCCs to keep up with the power factor or reactive power of the machine to a predefined set point.	Utilized restricted speed control via controlled external rotor resistance is fundamentally an induction generator.	The short-circuit behavior would be similar to Type 1.
Type III	These WTGs are fit for fluctuating the reactive power at a given active power and terminal voltage, which is capable of voltage control.	Has a reactive power ability compared to a power factor of 0.95 lagging (capacitive) to 0.90 leading (inductive) at	During the fault, the rotor power controller remains active, the machine stator currents would be limited between 1.1 to 2.5 p.u. of	The static and dynamic reactive power capability of type 3 wind turbines are determined with similar parameters (Qmax and

		the terminals of the machines? Or	the machine-rated current.	Q_{min}) and empowered when the wind turbine terminal voltage drops below 0.9 p.u. Users can adjust this value.
Type IV	Use a fast closed-loop turbine-level voltage control scheme.	can vary the grid side converter current, permitting control of the effective power factor of the machines over a wide range. Reactive power limit curves for different terminal voltage levels are normally given.	Currents during network faults will be limited to slightly above-rated current. This impediment is impacted by the power converter control and is generally vital to protect the power semiconductor switches.	Turbines incorporate extra parameters to account for the turbine converter's dynamic overload capability and are empowered when the wind turbine terminal voltage drops below 0.9 p.u. Users can adjust this value.
Type V	Using AVR each wind turbine control voltage at the collector bus or on the high side of the main power transformer. Usually, a centralized wind farm controller will manage the control of the voltage.	At power outputs below rated power, the reactive power output is only limited by rotor or stator heating, stability concerns, and local voltage conditions and it is unlikely that PFCCs would be required.	It seated the turbine control system to operate at grid standard.	Fault current contribution can range from 4 to more times rated current for close-in bolted three-phase faults.

2.7 Power Quality of Renewable Energy Systems and Their Integrations

The grid integration of renewable energy systems faces significant challenges with the presence of intermittent renewable power generation in the power grid. In such a way, power quality issues, especially harmonic distortion in distribution networks, are one of the major concerns of power utilities[37]. Such distortion is a serious power quality problem in the wind that may occur due to wind nature. The produced harmonics can result in parallel and series resonances, overheating power transformers, and the maloperation of control devices[38]. Another power quality issue is that the inter-harmonics appearing at a low harmonic range below the 13th harmonic may interact with loads in the vicinity of the inverter. Even harmonics, especially the second harmonics can probably add to the unwanted negative sequence currents that affect three-phase loads. In addition, variations in solar irradiation can cause power fluctuations and poor power quality[39].

It is vital to have a favorable technical and regulatory framework that could effectively manage the short-term and long-term challenges of large-scale wind farm penetration. The growth of wind power is limited in some parts of the world such as Ethiopia due to short-term and long-term problems. To overcome those issues there are grid codes and standards for integrating renewable power generation into a power grid. However, their maturity and periodic upgrade are important to plan and operate the future grid. Creating increased intermittent renewable power generation also stresses the reserve margins of the power grid into the operational impacts. Thus, the integration of renewables into a power grid problem needs robust and economic solutions for meeting the power system quality-related issues.

2.7.1 Integration

Quality power system operation is sustaining the energy supplied in balance with electricity demand.

- On short time frame scales (from milliseconds to minutes), the goals are power quality and voltage and frequency stability.
- On considerable time scales (from minutes to hours), the scheduled generation should satisfy the planned demand and the electricity generated required to reach the load.

- On longer time scales (from weeks to seasons), the generation and transmission capacity should be able to meet demand in all parts of the system over the entire year; otherwise, loads should be curtailed to keep the system in balance.

Power system planning for the interconnection of new generation resources ensures that there are adequate energy resources and conveyance capacity to interconnect new supply and that demand requirements are met reliably and efficiently manner for the planning horizon. As well as ensuring adequate resources and the ability to satisfy demand under typical operating conditions, system planning should also ensure that adequate reserves and vital system resources exist to reliably serve demand under credible contingencies such as the loss of a generating unit, a transformer, or a transmission facility.

There are usually limits on the harmonic currents that the wind farm can introduce into the network, and in this area, detailed analysis can be difficult. Ideally, the existing background harmonics on the network should be established, but these are often unknown. On weak networks, voltage steps, caused by wind turbines starting or stopping, or the energization of transformers, can be a problem. A related problem is voltage flicker, which can be caused by wind turbines starting or stopping, or when they are in continuous operation[40].

Power system planning needs to be adjusted to consider the increasing portion of variable renewable energy (VRE). Reliability-focused equipment standards are being developed to facilitate the integration of additional variable generation into the bulk power system. According to a reliability view perspective, a set of interconnection procedures and standards applies similarly to all generation resources interconnecting to the power grid. However, the ability of the generator owner and operator to provide the following functionality is essential for wind power:

1) Voltage regulation and reactive power capability

2) Low- and high-voltage ride-through

3) Inertial-response (effective inertia as seen from the grid)

4) Control of power ramp rates and/or curtailing of power output

5) Frequency control (governor action, automatic generation control, reserve, etc.)

The capacity and degree of variable generation to give the impact of the above function and how wind energy can be readily connected to the grid power system. Integration procedures perceive the specific behavior of variable-generation technologies but focus on the overall performance of the bulk power system rather than that of an individual generator.

2.7.2 Interconnection Stages

Connect wind power to the grid system is further classified into three major stages each with its own set of required studies:

1) Interconnection studies
2) Wind power design and modeling
3) Connection to the grid, commissioning, and testing

1) **Interconnection Studies:** A progression of studies is conducted to assess the proposed wind power plant's impact on the system. Screening study completion and a notification to continue from the interconnecting entity set into motion the Interconnection Studies process. Once the sub−synchronous resonance (SSR) study and full interconnection study (FIS) is finished, an interconnection agreement may be reached between the plant owner and the electrical utility or market operator.
2) **Wind Power Design and Modeling:** The electrical utility or market administrator models the new generation resource in a future planning base case. At this stage, the network model is built with the new resource node and a new network operations model to reflect changes from interconnection studies. Normally, the installation of telemetry points and the creation of a SCADA plan to establish real-time communication and control are required. In terms of market operations, the market operator also establishes polled settlement meter communication, which permits the gathering of real-time data for settlements.
3) **Connection to the Grid, Commissioning, and Testing:** The Generation Resource's Commissioning Plan, Request to Commission Point of Interconnection, Request for Initial Synchronization, and Request to Begin Commercial Operation are submitted and approved. After these steps, the actual plant is connected to the grid (transmission infrastructure might be built for this to occur). Typically, the acknowledgment of the test results showing the maximum leading and lagging reactive capability is expected for approval of commercial operation.

2.8 Smart Grid and Integrated Renewable Energy Systems

Smart grids and micro grids have been universally proposed as the future vehicle to facilitate grid integration of renewable energy[41]. The advantage of smart grids is that they provide a framework for advanced monitoring and control of the electricity grid at a micro-level. This reduces the number of barriers (especially economic) to implementing enabling technologies and ancillary services for renewable energy generation[42], [43]. Smart grid benefits are listed below;

- It can support demand management by coordinating loads on a home area network with pricing signals from the utility.
- It can coordinate storage technologies by determining appropriate times to store, import, or export energy.
- It can utilize dynamic line ratings since sag and temperature sensors can be installed in strategic locations along transmission lines.

The information from these devices can be used to calculate the line rating and communicated to smart protection devices to ensure that the line is overloaded. Smart grids often go hand in hand with microgrids which are sections of the grid capable of operating autonomously as well as in grid-connected mode. Successfully implementing a microgrid will require the application of smart grid technologies to ensure that distributed generation, storage, load, and distributed energy resources can be coordinated. Having an intelligent local grid will also facilitate renewable generation[42]. The interoperability standards for the implementation of the large-scale smart grids are :-

- Electric power- how electricity moves and devices interconnected
- Communications -how information is exchanged and devices communicate.
- Information -What data and information are exchanged and how it is organized?

The main goal of interoperability standards is to ensure that two components in a smart grid (devices, networks, appliances, etc.) can communicate and exchange information and data effectively.

2.9 International Wind Power Grid Code

The main objective of the grid code is to rule over power system operation and the energy industry furthermore it provides technical regulation. It enables network operators, power generators, suppliers, and consumers to function more effectively across the industry[35]. This ensures operational stability and security of supply and contributes to well-functioning energy wholesale markets.

Wind power interconnection requires a connection code that maneuvers generator connection, consumer Connection, HVDC Connection, operating, planning, and market of the power system network. Grid code is formulated based on a country's energy policy[44].

Grid codes can be developed for a grid operator's single control area, a country, or even an entire region, comprising one or even several synchronously interconnected systems. Wind power grid

codes may thus be very in-depth and technical content.

- **Good practice in grid integration code across the globe**

Europe has found a good practice in grid integration code which is the generation side grid requirements are similar to international grid code which should be established within the framework of a binding network code on grid connection, power producer required to meet a certain voltage for reliable operation their plant and access to the network to deliver their power, all at a cost-efficient access fee[45].

Furthermore, the power consumption has required to be met during operation the first voltage level at the connection point has to stay within an acceptable range as most customer appliances (e.g., lighting equipment, motors, computers, etc.) require a specific voltage range (e.g. 230 V ± 10 %) for reliable operation. Second, the power should be available at exactly the time the consumers need it to use their various appliances (i.e., when a customer switches on a certain device the electrical power starts to flow). Thirdly, consumed energy should be available at a reasonable cost (this should also include low external costs to reflect the environmental impact of electricity production)[46].

2.10 Grid Integration Requirements and Codes for Ethiopia

Ethiopia has a wind resource with velocities ranging from 7 to 9 m/s. Its wind energy potential is assessed to be 10,000 MW, which is moderately suitable for wind power. Currently, Ethiopian Electric Power has run three wind farm power plants (Ashegoda, Adama I, and II, wind farms) operating with a total installed capacity of 324 MW see Figure 2.0.3. Hence, globally Ethiopia's wind power installed capacity is placed at 54th place[47]. Furthermore, Aysha II and Assela wind farms are under construction and expected too operational soon. Presently, Ethiopia has a regional interconnection with Sudan, Djibouti, and Kenya so furthermore generation is an option to meet the demand

In Ethiopia to achieve energy security and sustainable development, Ethiopian Electric Power (EEP) has embraced wind power to meet its energy mix with Hydropower playing a very crucial role in achieving this set objective[38]. As Ethiopia's geography is convergent to the red sea, summer monsoon and tropical Easterlies contribute a significant amount of wind resources and power capacity. Moreover, Tana Lake, mountains, hills, plains, and gaps in the mountains can have comparable good conditions and locations for wind energy generation[48].

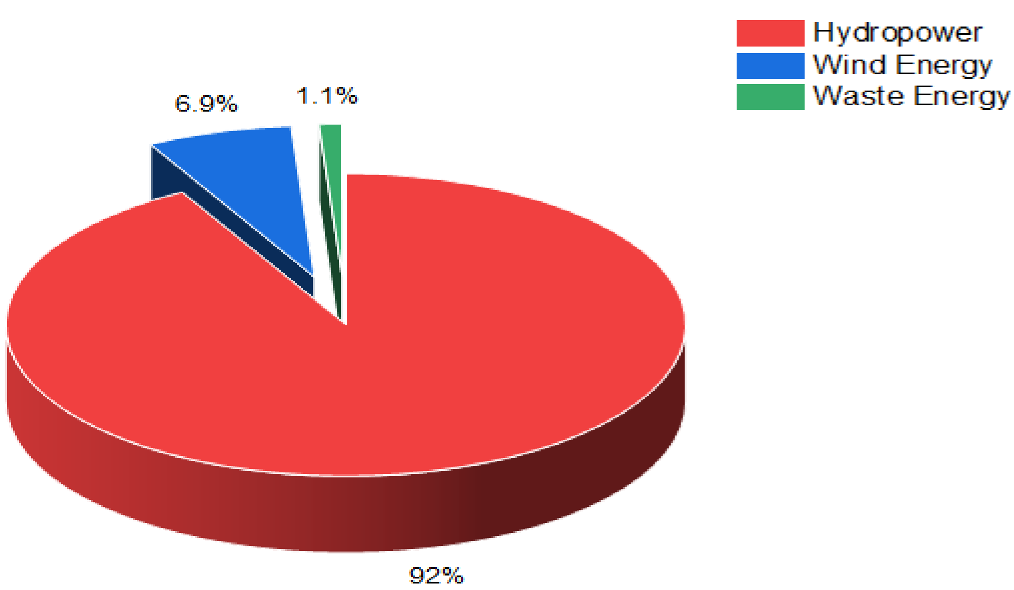


Figure 2.0.3: Ethiopia's energy sources share [49].

2.10.1 Ethiopia Grid Codes

For a sustainable and reliable power system, Ethiopia is applying a grid code between a power source and a common coupling point. Hence any power supply connecting to the network is adapted to meet the requirements. The current Ethiopia grid code contains shares and unique requirements are summarized in below Table 2.0.3.

Table 2.0.3: Ethiopia Grid code Renewable power plant (RPPs)[50]

Requirements	Description
Fault Ride-through	Conditions for which the RPP must remain connected, Active Power provision during a fault, Voltage support requirements during the disturbance, and Restoration of Active Power after the fault has been cleared
Remain Connected Voltage Condition	Medium and Large wind or solar photovoltaic RPP shall remain connected to the ENDS for voltage disturbances on any or all phases, where the system phase voltage measured at the HV terminals of the connection transformer remains above a specified level for a specified length of time
Active Power Provision During a Fault	During a voltage dip, the controllable RPP shall provide Active Power in proportion to retained voltage and maximize reactive current to the ENDS without exceeding its declared limits.
Ramp Rates	The RPP control system shall be capable of controlling the ramp rate of its active power output with a maximum MW per minute ramp rate set by the regional control center. There shall be two maximum ramp rate settings. The first ramp rate-setting shall apply to the MW ramp rate averaged over one 1 minute. The second ramp rate-setting shall apply to the MW per minute ramp rate averaged over ten 10 minutes

Reactive Power Capability	Reactive power capability is a Generating Plant’s capability to provide reactive support which is essential in maintaining an adequate system voltage profile for system reliability under normal and contingency conditions.
Active Power Control for Wind Generating Plants	. To prevent instability in the Distribution System, the Wind Turbine Generating Plant shall be equipped with an automatic downward regulation function making it possible to avoid a temporary interruption of the Active Power production at wind speeds close to the cut-out wind speed
Islanding	Intentional islanding of the RPP shall be permitted to provide uninterrupted service to local Customers during an outage. The protection system must be capable of protecting normal as well as islanding mode.
Power System Remain Connected Frequency Ranges	Frequency is the one parameter common to all members of a synchronous electric power system, and an accepted indicator of that system’s ability to balance resources and demand as well as to manage disturbances.

2.11 ADAMA II Wind Farm Grid Integration Performance Research Gap Summary

The main research gap in investigating ADAMA II wind farm grid penetration performance studies is the above-mentioned researcher conducted an impact investigation based on a single turbine of a farm analyzed and conclude. However, a large wind farm such as the ADAMA II wind farm shall be analyzed, and investigated each wind turbine of the farm's impact and performance on the grid. Hence, this study addressed each wind turbine's performance on the grid penetration of the Adama II wind farm by considering all 102 turbines of the farm. The summary of the works of literature is presented in below Table 2.0.4.

Table 2.0.4 ADAMA II wind farm performance research gap summary

N<u>o</u>	**Authors**	**Title**	**Methods Employed**	**Findings**	**Gap**
1	Teshale Tadesse	Study of doubly fed induction generator control under grid fault conditions	Modeling and simulating of the controller using Matlab/Simulink in wind turbine system integrated with grid system	After the clearance of the short circuit fault and voltage dip, the proportional integral controller manages to restore the wind turbine ‘s normal operation.	The study analysis only 6 WT turbine wind farm performance
2	Anchinesh Mengistu	Analysis of dynamic voltage stability on the penetration of ADAMA ii wind farm in Ethiopian grid	The modeling, simulation studies, and analysis has been done using Power System Simulator for Engineering (PSS /E) software.	Wind farms with voltage controllers can control the voltages at selected nodes in the high voltage grid.	The study conducted its investigation based on single wind turbine impact but as large wind farm impact is not analyzed
3	Esayas Meshesha Sisayu	Impact Assessment of Large-Scale Integration of Wind Power to the National Grid: The case Adama wind-farm-II	Aggregated model of grid-connected wind farm using MATLAB/Simulink tool and ETAP software.	Can improve transient stability margins, when being equipped with low voltage ride-through capability, reactive current boosting, and ideally with fast voltage control	The study conducted its investigation based on a single wind turbine impact but as large wind farm impact is not analyzed

4	Getachew Bekele, Abdulfetah Abdela	Investigation of Wind Farm Interaction with Ethiopian Electric Power Corporation's Grid	Developed using DIgSILENT Power Factory simulation tool.	Adama wind farm can ride from voltage deep within a short time. The active and reactive power performance of the wind farm is also good concerning three-phase short circuit fault	Each wind turbine impact did not investigate
5	Abraham Alem Kebede	Power Quality Impact Analysis of Wind Farms on Utility Grid, A Case Study in Ethiopia	Using Matlab software, the steady state harmonic load flow analysis of the wind farm at 33KV bus-bar system is performed	The power quality of the wind farm can be said to be good and does not have a significant negative impact on the power quality of the grid system at present.	The study is limited in scenarios it's not enough to conclude the farm is quality power issues with a limited attributes analysis
6	Abdulfetah Shobole, Muğdeşem Tanriöve	Fault Ride-through Capability of Wind Farm	The DigSILENT PowerFactory Simulation tool.	Adama Phase-1 with PMSG WT and Adama Phase-2 with DFIG WT type is feasible to integrate based on this study	Only the dynamic behavior of these wind turbines under fault conditions is studied hence it is limited to the scenario
7	Kassahun Tadesse Megra	Wind resource assessment at Adama II wind farm using wasp	Using the Wind Atlas and Application Program (WAsP) by applying wind flow modeling methodologies	The wind resource at Adama II is a wind class of 6	Only concerned with resource assessment, which did not conduct operational scenarios

8	Zenachew Muluneh* and Gebremichael Teame	Dynamic modeling and performance analysis of PMSG-based variable speed WTG: a case study of Adama wind farm I, Ethiopia	MATLAB Simulink using a dynamic mathematical model of the PMSG	The existing system model shows that the actual values of performance variables correspond well with the analytical values of the system.	The study analysis targeted PMSG turbine type wind farm
9	Debru Abeba Bayray, Mulu Molimas, Marta,	Adama-II wind farm performance assessment in comparison to feasibility study	The site potential was reassessed using WAsP software and the performance of wind turbine generators was investigated using 2 years of SCADA data	Due to Long-term correction data and weather conditions, there is a performance deviation investigated.	Limited in considering scenarios and data observation.

2.12 Wind Power Generation Forecasting

There is a lot of time scale or prediction horizon classification but below the listed time scale most literature is applied [51].

i. Immediate short-term (hours ahead) apply for real-time grid operation and regulatory actions.

ii. The second one is short-term (day a head) applicable for economic load dispatch planning, load reasonable decisions, and operational security in the electricity market.

iii. Long-term (years ahead) is applicable for forecasting maintenance planning, operational management, optimal operating cost, and determining future feasibility.

There are four methodologies to forecast future wind power production i.e. physical approach /deterministic approach used numerical weather prediction, a statistical approach, the machine learning approach, and the hybrid (combined physical and statistical approach using weighting, preprocessing, or decomposition techniques[52].

I. Physical approach

The physical approach is carried out using the manufacturer's power curve, wind flow inside and outside the wind farm, numerical weather prediction, sky imagery, and satellite image to predict wind power output[53]. It has numerous sub-models, which are subjected to translation from numerical weather prediction forecasts at a certain site location and a given turbine hub height. This approach is most suitable for long-term forecasting, as it's fairly sensitive to market information even if, it requires high computational cost and desires complex mathematical operational[54].

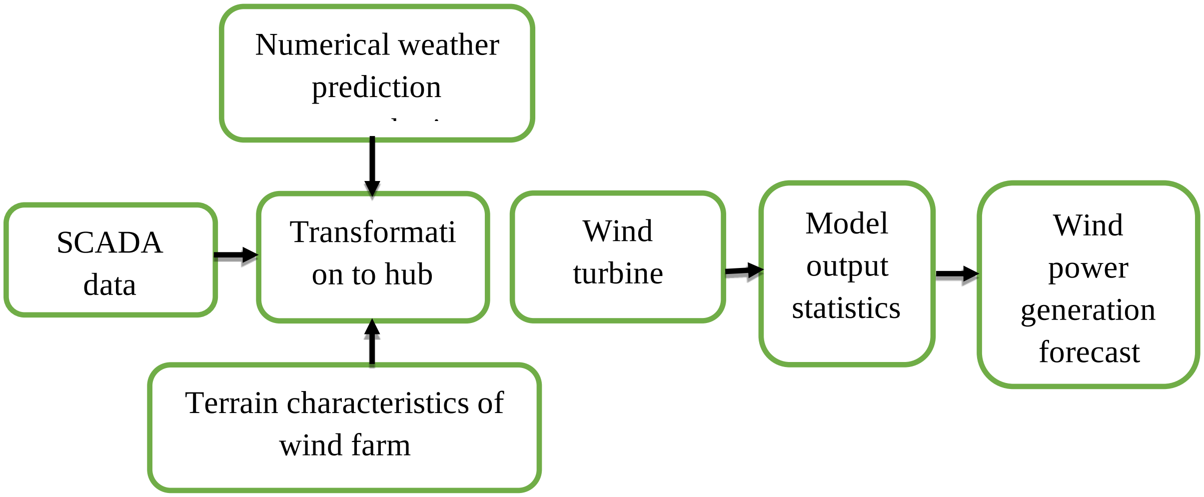


Figure 2.0.4: Physical approach [55]

II. Statistical Approach

A statistical approach is based on a sequence observation of one or more climatology inputs parameters measure at a certain time instant and combining those parameters such as numerical weather predictions of the temperature wind direction, wind speed, etc., with together real-time data of wind farm i.e., wind speed, wind direction, wind speed, power. This approach is limited by the prior assumption of a linear form among time series[56]. With numerous historical data to rely on the collection and processing of data in practice. This approach is reliable for short-term forecasting time series. There are several sub-models such as artificial neural network (ANN) such as multilayer perception (MLP), Markov chain, Fourier series, and regression methods such as Auto Regression Moving Average, Auto Regression Integrated Moving Average, and Seasonal Auto Regression Integrated Moving Average[57].

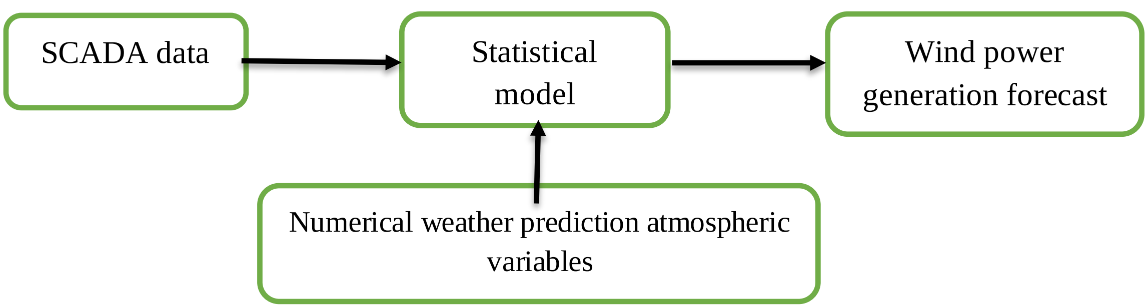


Figure 2.0.5: Statistical approach [55]

III. Hybrid Approach

The hybrid model is combining two or more different models to get high accuracy by reducing a single model's technical limitation such as combinations of ANN and NWP- based models along with a support vector machine (SVM). This model has been applied to short times such as for time horizons between 6 and 72 hours[58].

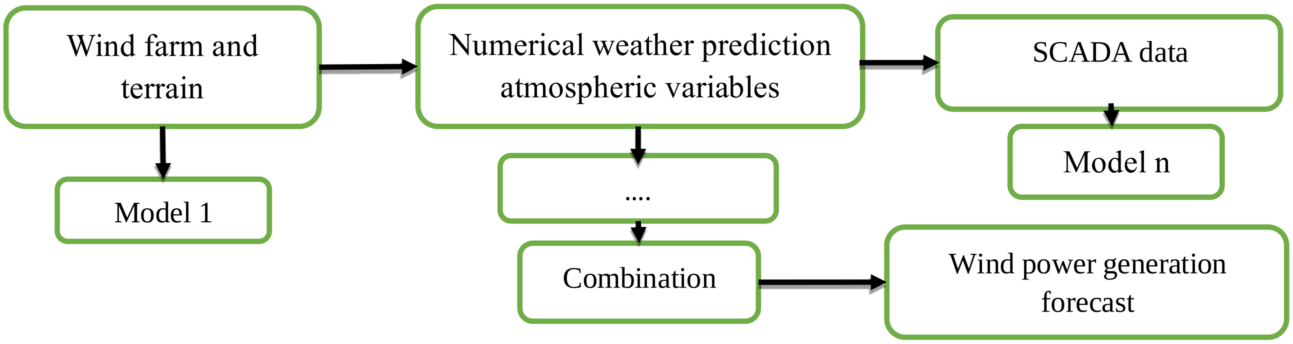


Figure 2.0.6: Hybrid approach[55]

IV. Machine Learning Methods

Machine learning is one forecasting approach based on algorithms and represents complex no-linear relations between outputs and inputs without predefined mathematical models[57]. It uses soft computing techniques such as artificial neural networks (ANN), fuzzy logic, support vector machine (SVM), and singular spectrum analysis (SSA). etc. to learn the relationship between the forecasted wind and power output from the time series of the past datasets and identify patterns to forecast outcomes or behavior[59].

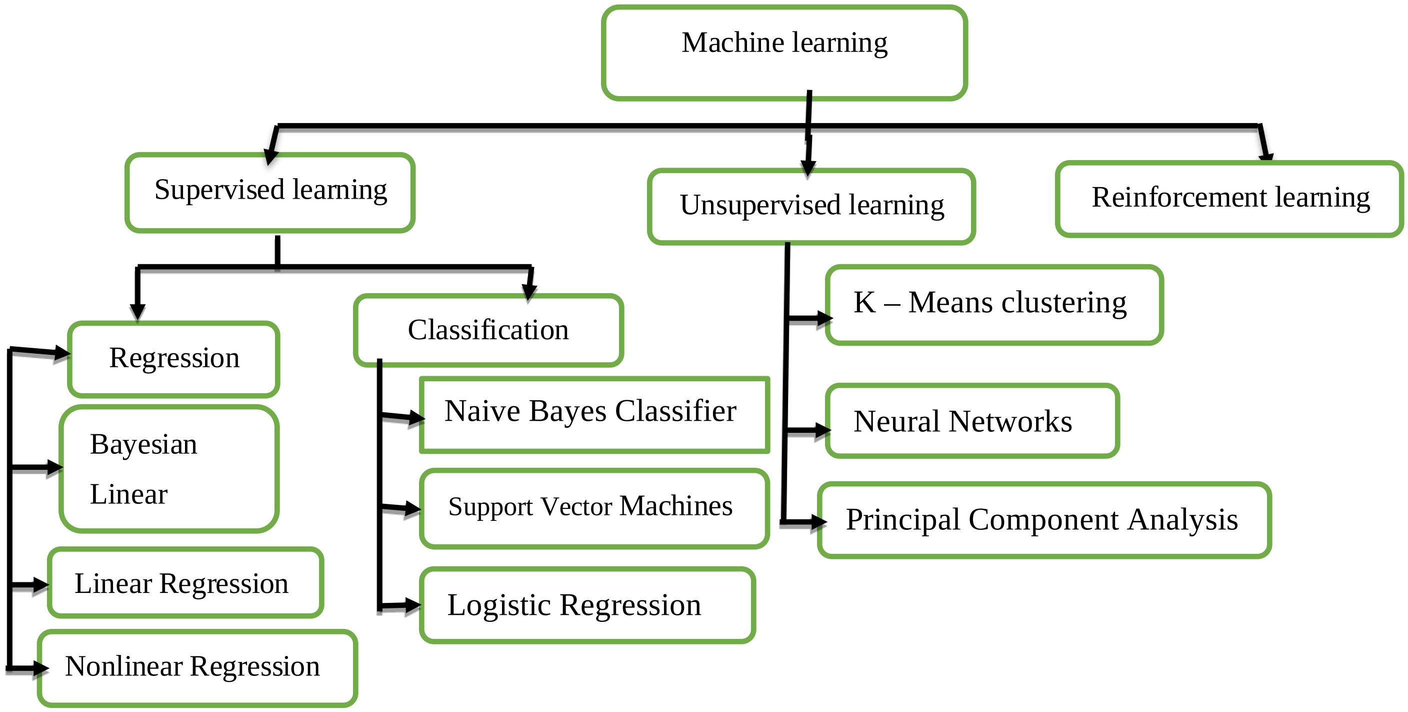


Figure 2.0.7: Machine learning classification [60]

- **Artificial Neural Networks**

Artificial Neural Networks (ANN) are forecasting methods applied based on simple mathematical calculations and it allows a complex nonlinear relationship between the predictors and their response variables. A neural network works as a network consisting of neurons that are organized in several layers. Namely, the input layer includes the predictors, and the output of layers forms the top layer. And also, there may be some intermediate layers in between which are called the hidden layers[61] [62].

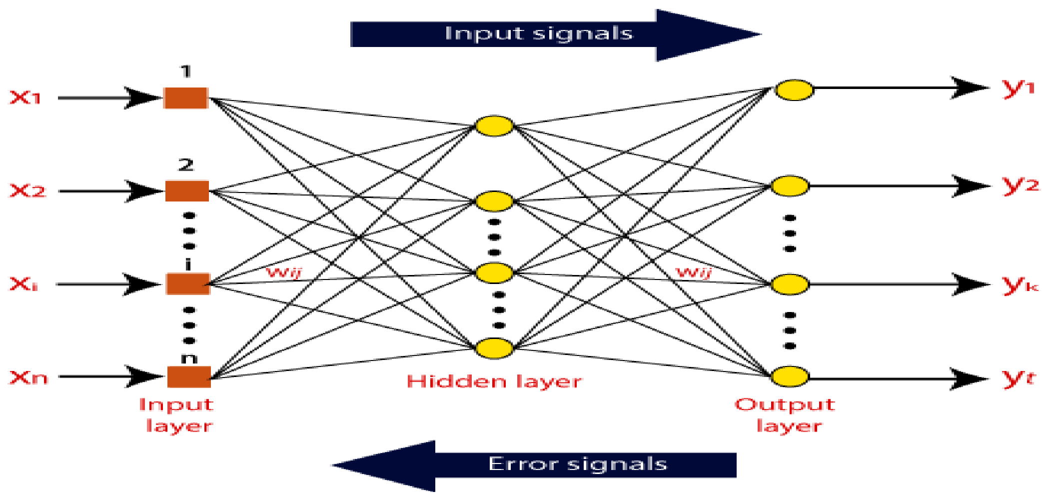


Figure 2.0.8: ANN schematic diagram[62]

- **Singular Spectrum Analysis (SSA)**

Singular spectrum analysis is a non-parametric spectral estimation method that uses no assumptions for the underlying process[63]. This model combines multivariate geometry, classical time series analysis, signal processing as well as dynamical systems. Furthermore, Singular spectrum analysis decomposes the original time series data to its major independent components, such as trend, oscillation behavior (periodic and quasi-periodic components) as well as noise, efficiently, which are used afterward for time series forecasting[64].

- **Deep Learning**

Deep Learning is a part of machine learning. It can be applied to any algorithm that specifically uses a multi-layer neural network, a deep network. For instance, there are numerous ways to solve problems using reinforcement learning. [65]. Deep learning is in contrast to" shallow" learning relative to decision trees linear regression, support vector machines, logistic regression, and boosting, it has an input layer and output layer, and the inputs may be transformed with manual feature engineering before training. In deep learning, between input and output layers, we have one or more hidden layers. Sun et al.[66] Presented a multistep wind power production forecasting model combined with a predictive deep belief network and optimized random forest to predict up to 24-hour ahead wind power. Abdulelah Alkesaiberi [67] proposed a machine learning model using a dataset training set and a testing set. He trains using a 5-fold cross-validation technique to train the models and Bayesian optimization is employed to determine the values of the hyperparameters in the considered models. The model accuracy is evaluated R-square -0.96225, RMSE-105.1754, MAE-49.55875, and MAPE -26.53435.

2.13 Long-Term Wind Power Production Forecasting

Long-term (years ahead) forecasting is applied to safe grid integration, utilized power generation both light load and peak load, conducts maintenance planning, operational management, optimal operating cost and determines future feasibility. Hence several scholars have investigated and conducted many different models.

2.13.1 Wind Power Long-Term Forecasting Method Using a Physical Approach

Hanif et al.[68]Although physical approaches are more complex and need considerable computing resources, it is reliable for medium to long-term forecasting. Fruh W. [69]investigated a combined current state with knowledge of the long-term climate situation. This study used persistence, a linear model, or a model based on the mean daily cycle extracted from the long-term record. Although the model result was able to predict the correct output within a 10% error. integration. Sapronova et al. n.d. [70] presented 6 to 24 hours ahead of wind power production forecasting using computational fluid dynamics and bridge mesoscale weather prediction data models. Prosper et. al[71]This paper tests the effectiveness of WRF in evaluating the energy production forecasting of a wind farm in complex terrain, in real-time and analyses the representation of wake effects with the WF-S scheme on this particular wind farm as well as on its nearby surroundings.

2.13.2 Wind Power Long-Term Forecasting Method Using a Statistical Approach

Marulanda et al. [72] presented a spatial-temporal dependency methodology in multi-area markets to generate realistic wind power scenarios for the long term. Kennedy et al. n.d [73]Presented a chronological wind-plant simulation model to generate wind power time series of random lengths that accurately reproduce short-term (hourly) to long-term (yearly) statistical behavior though it did not consider turbine wake effect on power production. Mu et al.[74] presented wind speed spatial dispersion impact on the total wind power of a wind farm. Kritharas et al. [75] the study presents four parsimonious models and applied 52 years of data from seven stations across the UK and provided both autocorrelation and seasonality achieving the smallest errors.

2.13.3 Wind Power Long-Term Forecasting Method Using Hybrid Approach

Ahmadi et al.[76]Investigated the impact of input data on forecasting accuracy and developed three models based on a tree learning algorithm for six-month-ahead wind power forecasting models. The study results were longer time intervals and height extrapolation decreased wind speed forecasting accuracy. Penfield n.d.[77] Investigated ultralong term forecast of wind power production using a combined model of physical models and deep learning. It provides accurate performance for 7-day ahead of operational dispatching planning in electric utilities.

Azad et al.[78]resented statistical and neural network-based approaches to forecasting hourly wind speed data of the subsequent year. The performance of the developed model results in 0.8m/s mean absolute error (MAE). Dong et.al.[79] Presented a new hybrid model for long-term wind speed forecasting through a combined first definite season index method and the Autoregressive Moving Average models or the Generalized Autoregressive Conditional Heteroskedasticity forecasting models. Mehdizadeh et al.[80]Presented moving average (MA), autoregressive (AR), and autoregressive moving average (ARMA). The proposed models are used to estimate short-term (i.e., daily) and also long-term (i.e., monthly) wind speeds. Dhaheri et al.[81]Presented Auto Regression Integrated Moving Average and Seasonal Auto Regression Integrated Moving Average models, Artificial Neural Networks (ANN), and Singular Spectrum Analysis (SSA) models. The results obtained from SSA provide the most accurate forecasted values compared to the other three models. Ouyang et al. [82]Presented a modified ramp prediction model using an event detection framework. A multivariate model is applied data-mining algorithm to correct system errors of the first stage prediction. Saroha et al.[83] Investigated a hybrid of Linear Neural Networks with Tapped Delay and wavelet transform for probabilistic wind power forecasting two years ahead of a time series framework. The study result obtained MAPE is 6.23%. and simulation time taken is 2.914 seconds. Nie et al. [55]Present a combined approach of nonlinear combination-based point prediction and probability fuzzy clustering-based interval prediction of wind speed. The study uses variational mode decomposition (VMD) to decompose wind speed sequences and perform de-noising and reconstruction to generate a time sequence.

2.13.4 Wind Power Long-Term Forecasting Method Using Machine Learning Algorithms

Peiris et al.[84] Presented artificial neural network (ANN) models to forecast wind power generation in Pawan Danawi wind farm, Sri Lanka. It used wind speed, wind direction, and ambient temperature as the independent variables for the ANN models and produced wind power as the dependent variable. Khatib et al.[85]Presented, a long-term wind power production profile develops a cascade-forward neural network, support vector, and random forests machine learning algorithms models. for Jericho, Hebron, Jenin, and Ramallah cities of Palestine based on Nablus city wind data. Maroufpoor et .al[86]investigated six different heuristic model performances namely, ANFIS with subtractive clustering (SC), multilayer perceptron artificial neural networks, (ANN), adaptive neuro-fuzzy inference system (ANFIS) with grid partition (GP), generalized regression neural networks (GRNN), gene expression programming (GEP) and multivariate adaptive regression spline (MARS). Singh et al.[87] The proposed machine learning model for forecasting 6-month wind power data through extrapolating actual wind speed with 10-min intervals to hourly standard deviations and mean wind speed. Barbounis et.al.[88] Presented three local recurrent neural networks model using meteorological data to forecast wind speed a 72-time steps ahead, i.e., the infinite impulse response multilayer perceptron the diagonal recurrent neural network, and the local activation feedback multilayer network (LAF-MLN). Madhiarasan et al.[89] Presented a long-term wind speed forecasting model using an improved spike prop algorithm incorporating a spiking neural network (SNN) and improved modified grey wolf optimization algorithm (IMGWOA) based hybrid technique (SNN-IMGWOA). This study proposed a spiking neural network optimized through an improved modified grew wolf optimization algorithm.

Xu et al. [90] Presented the WRF model to obtain the numerical weather forecast and the gradient boosting decision tree (GBDT) algorithm to improve the near-surface wind speed post-processing results of the numerical weather model. The study tested result was the root mean square error (RMSE) of wind speed can be reduced from 2.7–3.5 m/s in the original WRF result by 1–1.5 m/s. Ahmed et al.[91]Develop a Gradient Boosting Machine (GBM) and Support Vector Machine (SVM), along with the regression model Multivariate Adaptive Regression Splines (MARS), to forecasting medium and long-term. This study tested the result even though SVM does have a better performance over other models to a greater extent for substantial uncertainty in the dataset but suffers from larger computational run time. Navas et.al [92]Investigated Radial Basis Function Neural Network (RBFNN), Multi-Layer Perception Neural Network (MLPNN), and Categorical Regression (CATREG) in Coimbatore, Tamil Nadu, India. This study considered various atmospheric factors and random variables as a parameter using SPSS software. [93] Proposed long-term wind power forecasting based on an adaptive wavelet neural network model. The study used a Multi-Input Single-Output (MISO) training approach and efficient performance compared with the persistent approach. Shuai Xiao[94]Proposed the correlation coefficient method to select reliable meteorological variables based on a data compensation model. The study established the RBF neural network to map the relation between weather data and historical power to get years of fitting power data. The study metrological variable was wind speed, wind direction, temperature, and pressure and the model was validated with actual Nanshan wind farm data, China. Du et al.[95]investigated rainfall forecast based on Support Vector Machine with Particle Swarm Optimization model and used traditional precipitation to replace the linear threshold. The study applied PSO to find the optimal parameters for SVM.

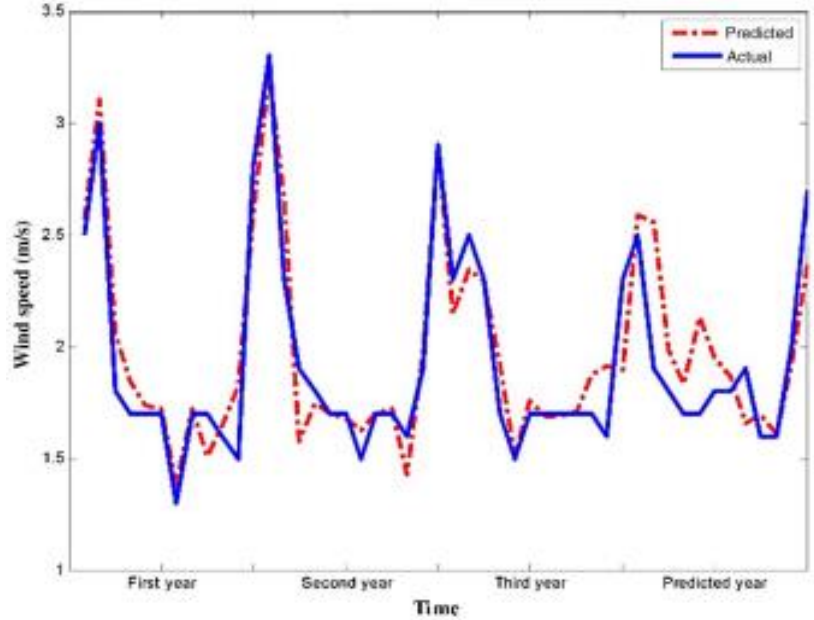
Although the above studies provide so many solutions, there are still many problems for wind power from a forecasting horizon perspective. it was investigated that the proposed machine learning methodologies in the literature studies mainly focused on very short-term and short-term forecasting. Short-term horizons of forecasting have various vital applications related to maintaining the stability of the microgrid. But long-term forecasting horizons are also essential for studying the economic feasibility of wind power integration into the electricity sector. Thus, a higher focus on longer-term forecasting is required and It could improve the incorporation of wind power into the electricity grid networks.

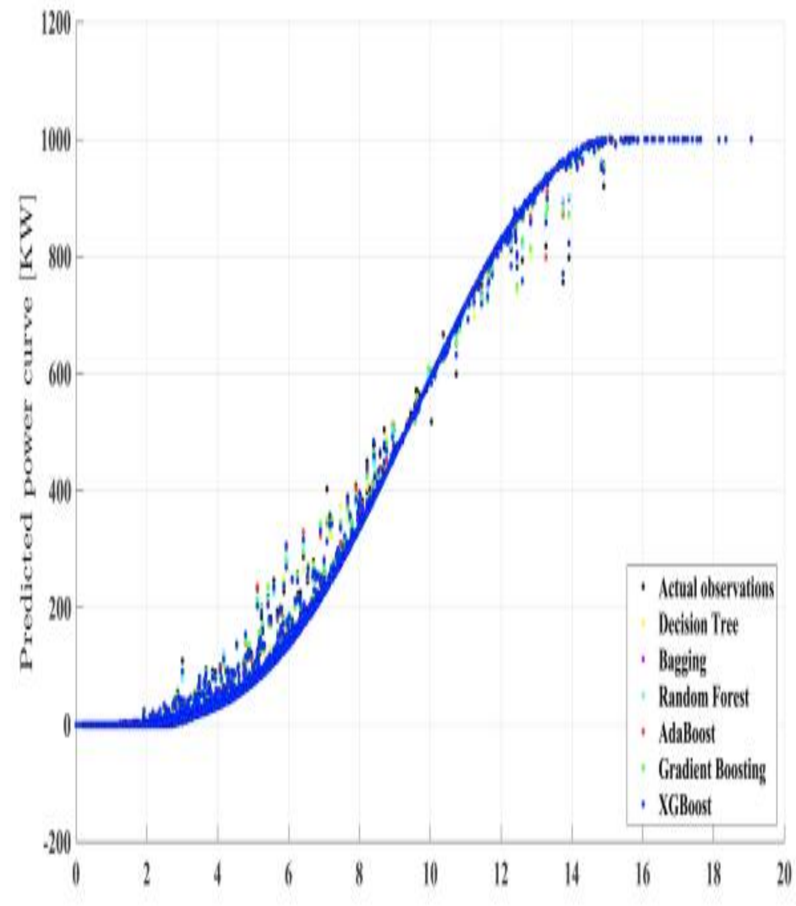
Forecasting wind power generation is a global concern and a critical issue for wind power conversion systems as it has a great influence on the scheduling of power systems as well as on the dynamic control of wind turbines. In Ethiopia's context even though there are three operational wind farms namely Adama I, II, and Ashegoda wind farms, it’s difficult to find literature related to future power forecasting for reliable grid operation. Furthermore, there are not enough studies have been conducted on Adama II wind farm national and regional grid integration performance, and specifically, long-term wind power production didn’t conduct a study on properly scheduled maintenance, optimum tower operation, and reliable system operation.

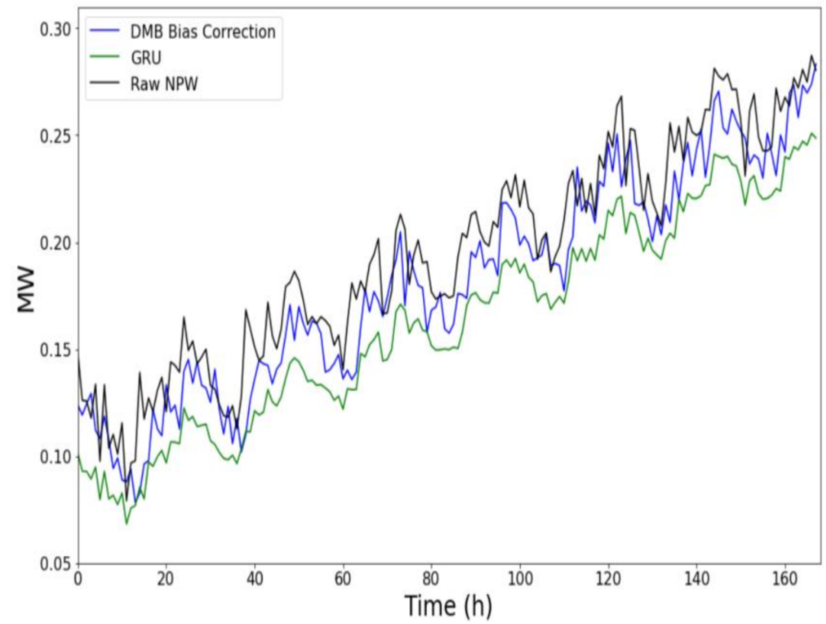
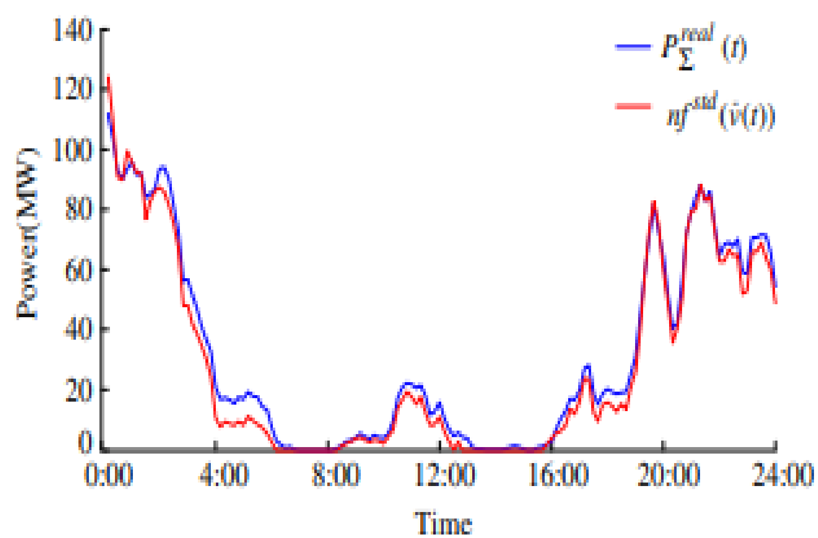
2.14 Power Generation Forecasting Research Gap Summary

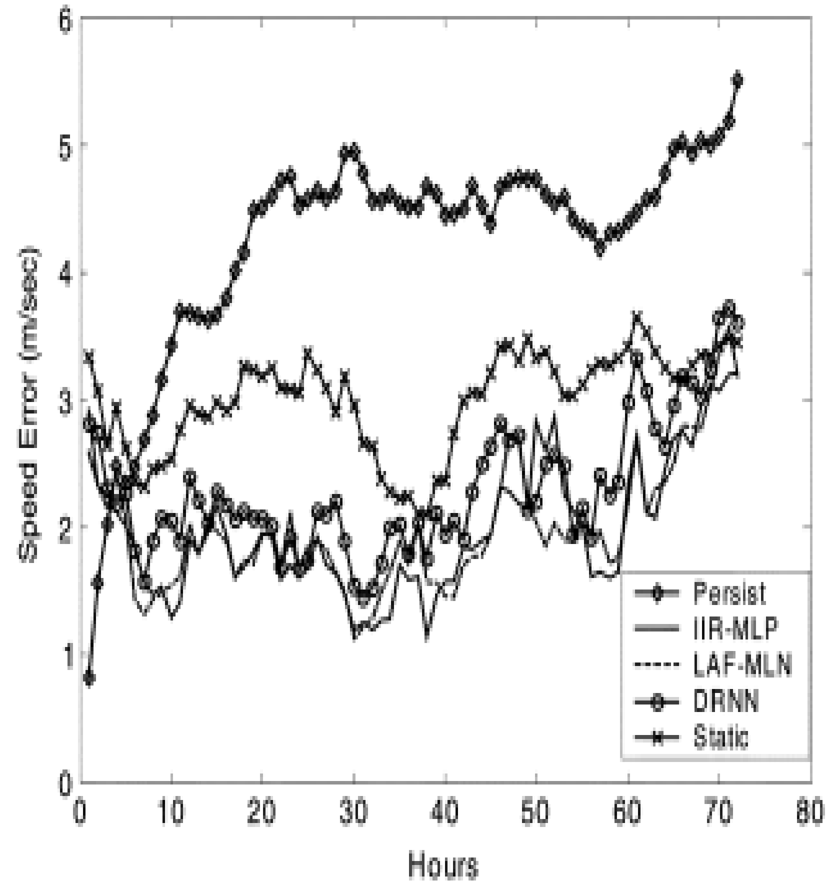
The main research gap of the above review research in long-term forecasting is prediction accuracy MAPE values > 15% and the period of prediction is a short period which is less than 6 months. The work of the researcher is summarized below in Table 2.0.4. In this study, the problem of long-term one-year ahead wind power forecast is addressed, based on machine learning model wind speed and outdoor temperature as independent variable inputs. This thesis intended to study sustainable power supply, and safe national and regional electric power integration performance by developing high-performance long-term forecasting of Adama II wind farm power production. This yearly ahead of power production forecasting would provide proper scheduling maintenance, optimum tower operation, and reliable system operation. The tools applied in this thesis are a machine learning algorithm with the python programming language with an anaconda environment for the proposed model development because it is easy to learn and code. The study used NumPy, DateTime, panda TensorFlow, Matplotlib, and stats model libraries and modules. A set of 6 years of wind power SCADA time series data of Adama II wind farm is used to train and test the data set.

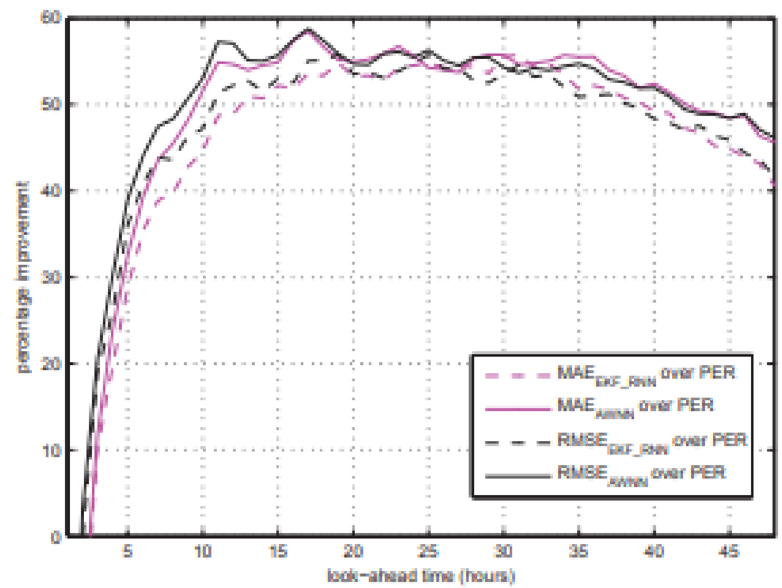
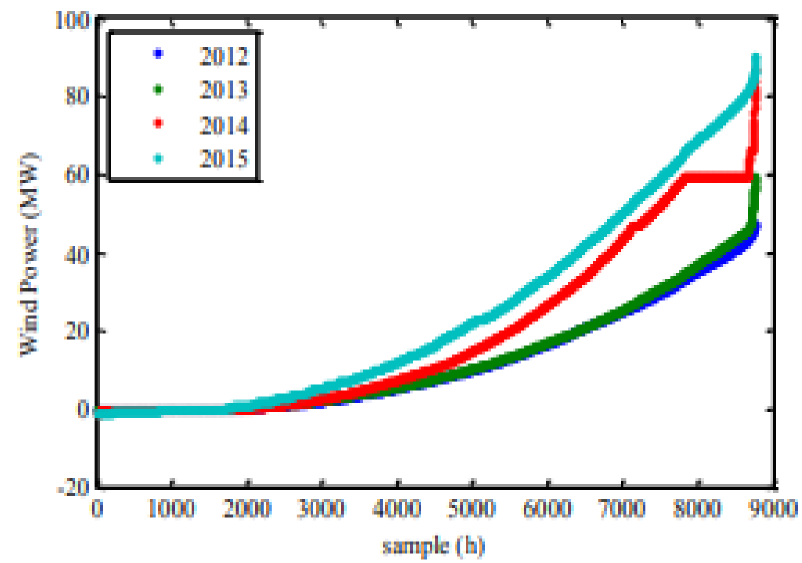
Table 2.0.5: Wind Farm Power Generation Long Term Forecasting Research Gap

No	Authors	Title	Method Employed	Findings	Gap	Output Power Curve
1	Hanieh Borhan Azad, Member, Saad Mekhilef, Senior Member, and Vellapa Gounder Ganapathy, Member,	Long-Term Wind Speed Forecasting and General Pattern Recognition Using Neural Networks	Applied statistical and the neural network-based approaches	very small mean absolute error (MAE=0.8)	Low predicting performance	

2	Amirhossein Ahmadi, Mojtaba Nabipour, Behnam Mohammadi-Ivatloo, Moradi Amani, Seungmin Rho, And Md. Jalil Piran	Long-Term Wind Power Forecasting Using Tree-Based Learning Algorithms	6-month-ahead wind power forecasting models using a tree-based learning algorithm	Tree-based learning algorithms can be successfully adopted Not only for long-term wind power forecasting but potential wind power forecasting at different heights And geographical locations.	Low accuracy and seasonal variation do not consider	

3	Julia Penfield	Ultra-long-Term Wind Farm Generation Forecast by Combining Numerical Weather Prediction with Gated Recurrent Units	Apply physical Models in combination with ML deep learning	Provides promising improvement in forecasting accuracy for 7-days ahead.	Seasonal variation doesn’t consider in a week's prediction	
4	Zhenhai Guo,Yao Dong, Jianzhou Wang, and Haiyan Lu	The Forecasting Procedure for Long-Term Wind Speed in the Zhangye Area	Hybrid definite season index method and the Autoregressive Moving Average (ARMA) models	Simple and quite efficient for daily average wind speed forecasting of Hexi Corridor in China	Daily base predication rather than hourly to analysis hourly variation	

5	Thanasis G. Barbounis, John B. Theocharis, Member, Minas C. Alexiadis, and Petros S. Dokopoulos, Member,	Long-Term Wind Speed and Power Forecasting Using Local Recurrent Neural Network Models	The infinite impulse response multilayer perceptron (IIR-MLP), the local activation feedback multilayer network (LAF-MLN), and the diagonal recurrent neural network (RNN)	It assures continuous stability of the network during the learning phase and exhibits improved performance compared to the conventional dynamic back propagation	Limited independent variable	

6	Bhaskar Kanna, Sri Niwas Singh	Long Term Wind Power Forecast Using Adaptive Wavelet Neural Network	An adaptive wavelet neural network is applied for mapping the NWP's wind speed and wind direction forecasts to wind power forecasts.	A significant improvement over the persistence method is achieved	Low-performance RMSE values Persistence - 20.9474 RNN- 15.1073 AWNN - 14.3516	
7	Shuai Xiao, Jiping Lu, Dian Li, Hua Yu, Mengjiao Li, Jialin Liu	Long-Term Wind Power Forecasting Based on Multi Model by Multi Meteorological Variables Based on Data Compensation	Use multi-meteorological variables based on data compensation. the model uses the correlation coefficient method to select the optimal meteorological variables	The applied model is effective and practicable, and it builds the foundation for analyzing the long-term wind power event		

CHAPTER 3: METHODOLOGY

3.1. General Framework

The main objective of the thesis is to examine Adama II wind farm grid integration performance in different scenarios of the farm and forecast one year ahead of power production. The study performs its modeling Adama II wind farm using MATLAB and Simulink to analyze its energy production performance. To get a means to mitigate technical and operational risk by enabling the engineering team to explore design tradeoffs, assess control and management system operation, and estimate achievable production with confidence. Furthermore, to perform fault studies in a safe and repeatable environment. The wind farm modeling can be done using two methods one is dynamic modeling which is the collected aggregation method and the other is modeling each wind turbine individually. Increased levels of penetration, place an increased emphasis on scrutinizing the impact that wind power connection has on grid reliability and stability. Furthermore, the study forecasted one year ahead of power production using machine learning-based SARIMA and then extended to linear regression, random forests, and XGBoost to see whether or not these linear and non-linear approaches can model our time series accurately to forecast the Power output of the wind turbine. The required data were collected from the Adama II wind farm SCADA database.

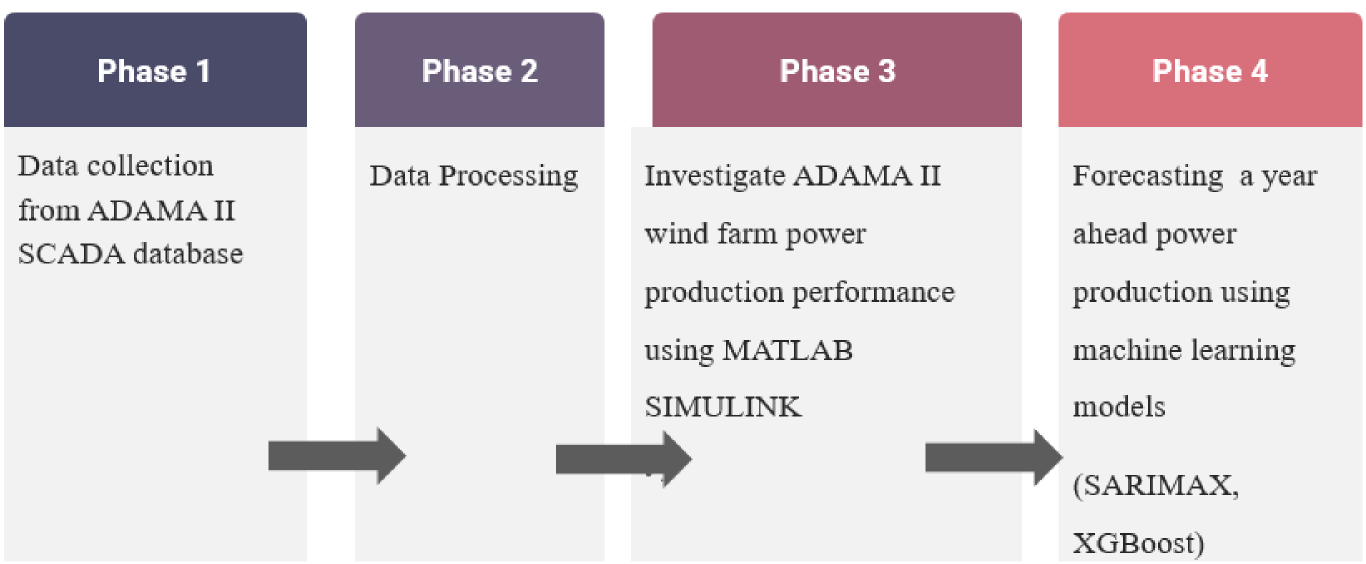


Figure 3.0.1. Methodology

3.2. Data Collection and Processing

For this study, both meteorological and wind farm power production data were collected from the farm SCADA. This study systematically selected 16 wind turbines from 102 turbines of the Adama II wind farm and 52608 data sets for six consecutive years (i.e 2016 to 2021) were collected.

3.2.1 Data Collection Interval

Although the SCADA data set provides five minutes time interval of wind speed, wind direction, outdoor temperature, and production power values for each turbine tower, the study converts it into daily mean wind speed values and standard deviations. Moreover, from the daily power function find out daily total wind power values using hourly wind power values see Figure 3.0.2. and data description is shown in Table 3.0.1

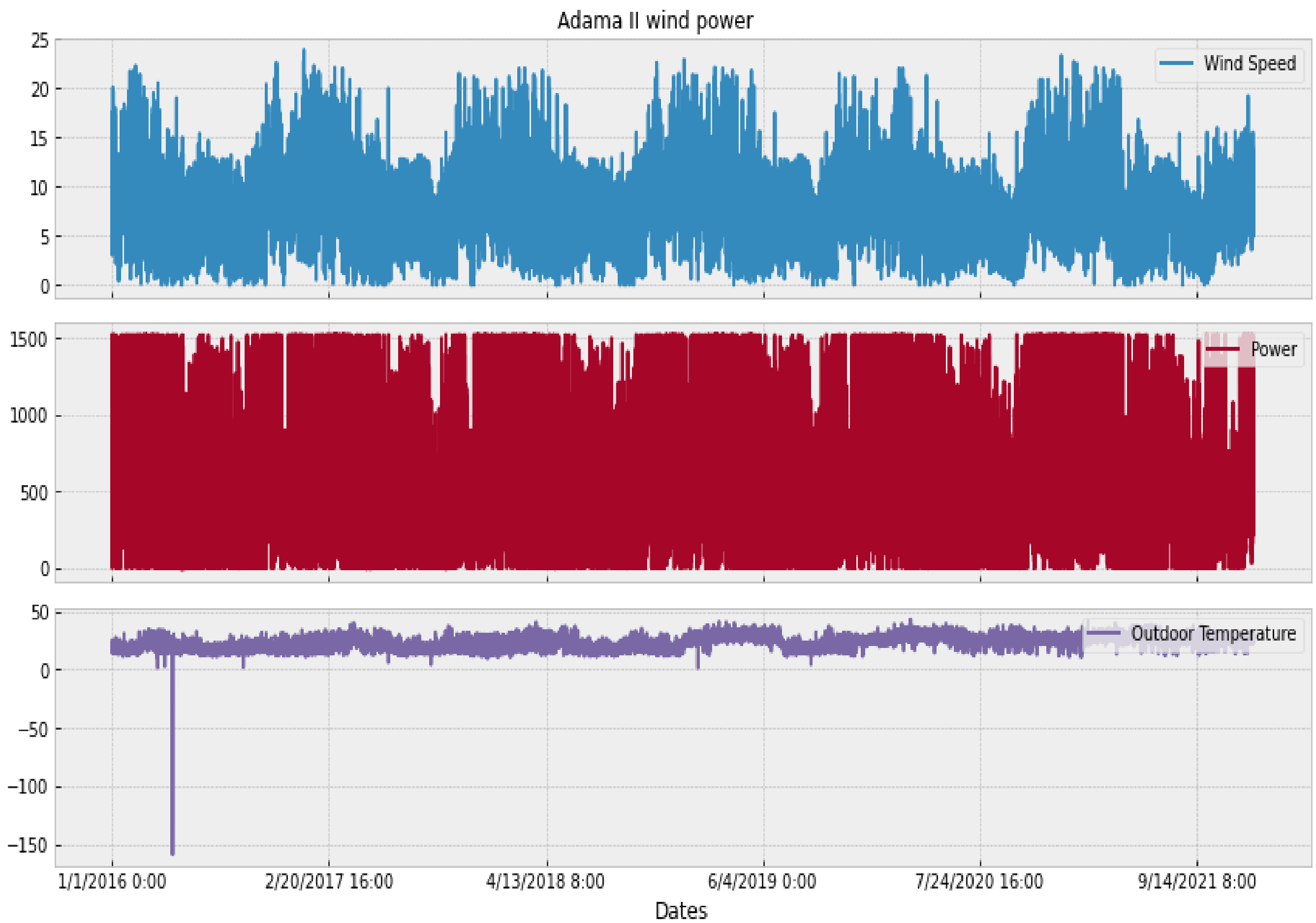


Figure 3.0.2 Adama II wind farm operational power data (2016-2021)

Table 3.0.1: Adama II Wind Farm Data analysis (2016-2021)

Variables	Stats							
	count	**mean**	**Std**	**min**	**25%**	**50%**	**75%**	**max**
Wind Speed(m/s)	52608.00	8.29	3.37	0.00	6.00	8.40	10.40	23.90
Power (KW)	52608.00	635.08	465.91	-9.00	221.30	595.90	977.13	1523.90
Outdoor Temperature(c^0)	52608.00	22.92	5.53	158.80	18.30	23.00	26.90	43.40

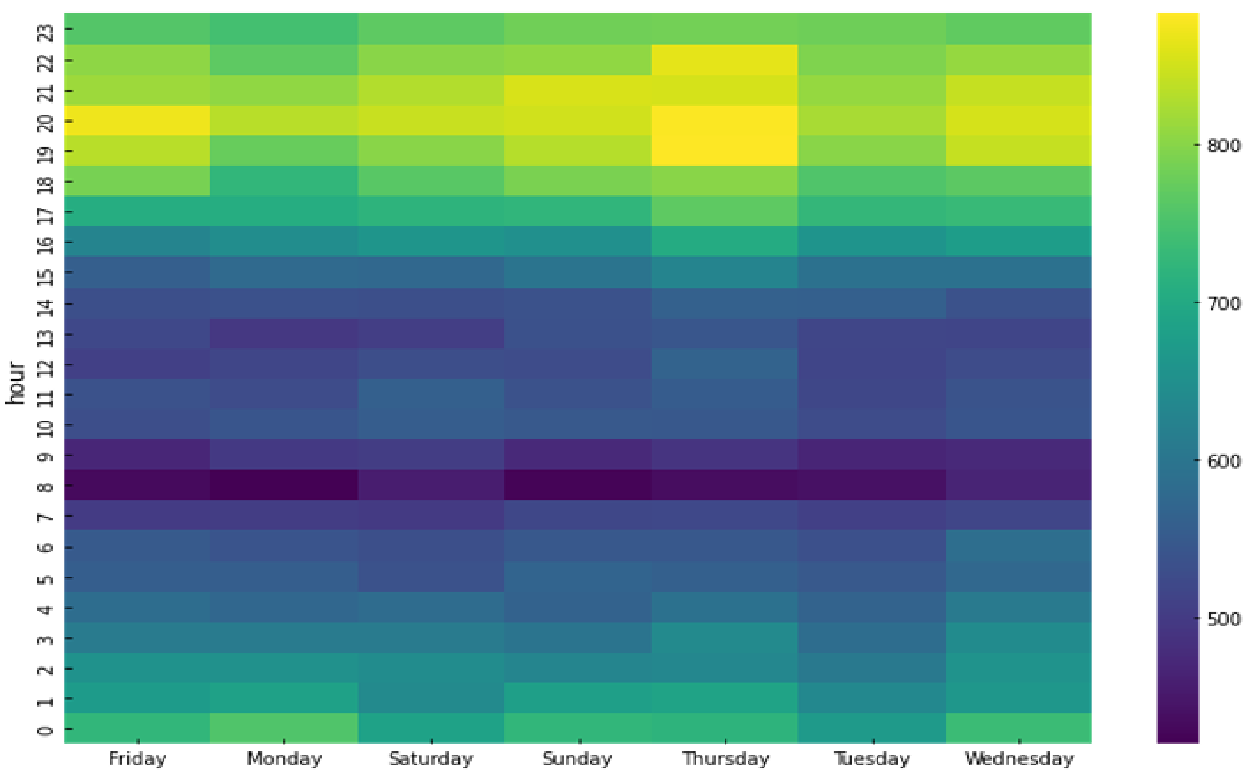


Figure 3.0.3: Average power production for each weekday averaged over 6 years (2016-21)

3.2.2 Sample Size and Sampling Technique

The sampling technique that's right for the study depends on turbine performance history starting from commissioning. The study applied a systematic sampling and cluster sampling method to choose the sample members of 102 turbines taken clustered into 8. The two best-performed wind turbines and the data available from each cluster are S12, S15, and S23. S02, N02, N04, N36, N21, N35, N49, N52, N57, N60, N68, N78, and N44. The sample turbine is representative of each cluster.

3.2.3 Data Quality and Homogenization

Time Series data holds a lot of information, but generally, it is not visible. The common problems associated with time series are unordered timestamps, missing values (or timestamps), outliers, and noise in the data. of all the mentioned problems, handling the missing values is the most difficult one. Since the conventional imputation (A technique used to take care of the missing data by replacing the missing values to retain most of the information) methods are not applicable while working with the time series data.

The wind farm data collected from the SCADA system contains several outliers, noisy data, and missing values caused by inevitable factors. Hence to filter true information the data require the study applied decomposition to appropriate preprocessing because it could easily decompose original data into time series with different frequency components to provide quality input for machine learning [96].

3.2.3.1 Missing Values Processing

We found 240 missing values of power, wind speed, and outdoor temperature hence we were handling those missing values in our time series data is a challenging task. Conventional imputation techniques are not applicable for the time-series data since the sequence in which values are received matters. Interpolation is a commonly used technique for time series missing value imputation. It helped us to fill the missing input data due to maintenance and any other related reason, by taking from the other year's data (2016, 2017,2018,2019,2020, and 2021) time-based interpolation applied. Based on the available variables around the missing value and their relationship. We only have 240 missing values. Since this is wind turbine power production data, hence the power production of wind turbines is climate dependent and changes depending on the minutes of each hour and day, day of the week, month of the year, season, and the year itself. So, field the missing values with the average values of the matching month and weekday for the same hours from the rest of the data for that year.

3.2.3.2 Noisy Data Cleaning

Noise elements in a time series can cause significant problems, and noise removal is highly recommended before building any model. The process of carefully minimizing the noise is called denoising. Fourier transform and rolling means are commonly applied for time series data. It has been used to clean the data rolling mean because it is simply the mean for a window of previous observations, where the window is a sequence of values from the time series data and also most researchers applied. The study applied the rolling mean method for data below 3.5m/s wind speed power values seated into 0MW and take mean power values for above 25 m/s wind speed to noise values. It has calculated the mean for each ordered data and it greatly helped in minimizing the noise in the time series data.

3.2.3.3 Outlier Detection in Time Series

An outlier in time series refers to a sudden peak or drop in the trend line. It has not concerned with the factors causing the outliers, but certainly, there can be multiple factors. It has to keep confined to the detection of outliers. There are different methods for detecting outliers namely, isolation forest, K-means clustering, and rolling statistical bound-based approach.

This thesis applied a rolling statistical bound-based method to properly treat the Adama wind farm data. The selected method is the most intuitive and works for almost all kinds of time series. The method works by creating upper and lower bounds based on specific statistical measures like mean and standard deviation, Z and T scores, and percentile of the distributions. The bounds are created on a rolling basis, like considering a continuous set of observations to create bounds and then shifting to another window. It has easily detected outliers and it was highly effective.

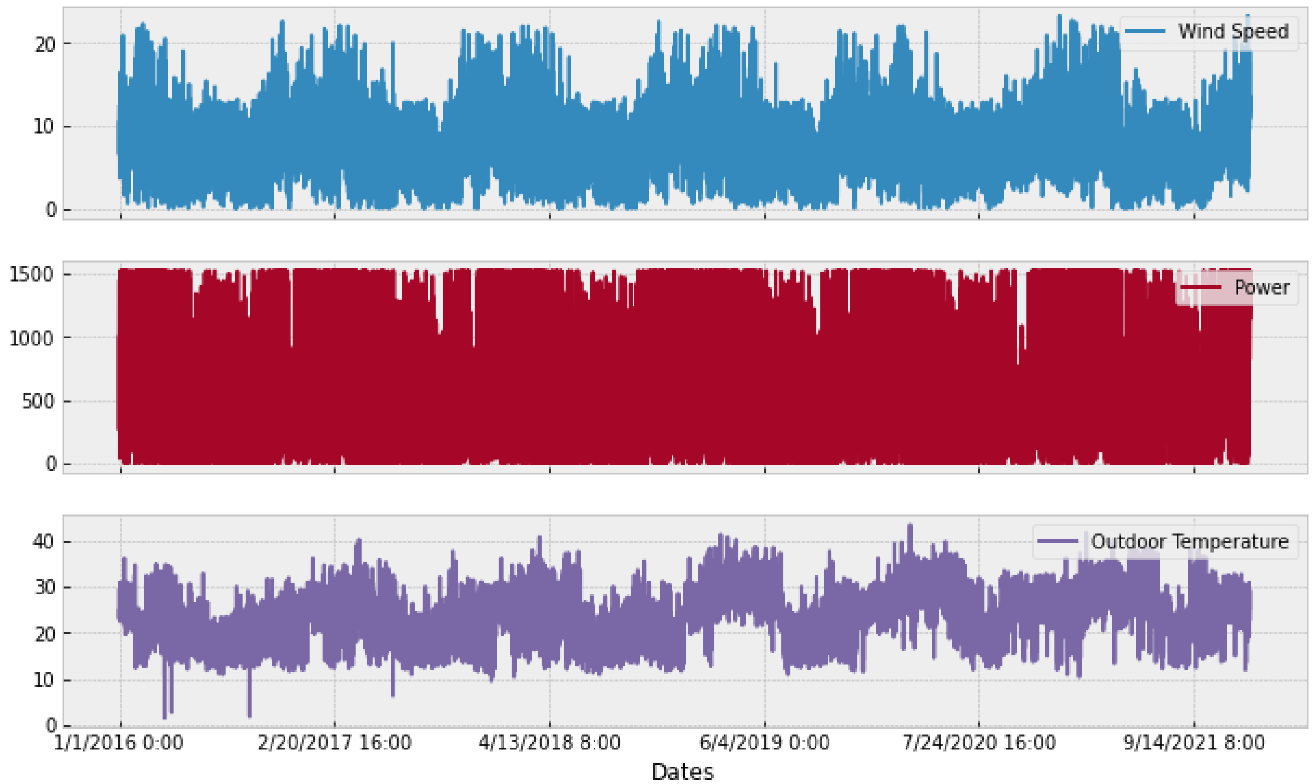


Figure 3.0.4: Cleaned data

As shown in above Figure 3.0.4 after processing the data it has to get cleaned data which is suitable for machine learning modeling. Furthermore, the cleaned data description is demonstrated in Table 3.0.2.

Table 3.0.2: Cleaned data description

Variables	Stats							
	Count	Mean	Std	Min	25%	50%	75%	Max
Wind Speed(m/s)	52608.0	8.27	3.35	0.00	6.00	8.30	10.40	23.30
Power (KW)	52608.0	640.33	471.27	0.00	219.80	592.95	1000.30	1523.90
Outdoor Temperature(c^0)	52608.0	22.98	5.43	1.50	18.50	23.10	26.90	43.40

3.3 Grid Integration Performance Investigation

3.3.1 ADAMA II Farm Grid Interaction Model

Modeling and simulation studies of a wind farm offer a means to mitigate technical and operational risk by enabling the engineering team to explore design trade-offs. Furthermore, able to assess control and management system operation, estimate achievable production with confidence, and perform fault studies in a safe and repeatable environment. This section analyzes and investigate Adama II wind farm energy production potential, downtime, output performance at different wind speed, and its impact on-grid system and propose a measure that can be taken to minimize the observed impact.

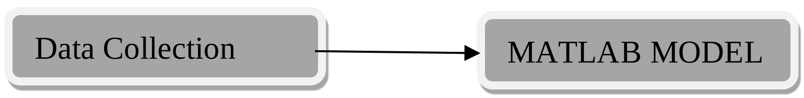


Figure 3.0.5: Methodology to analyze Adama II wind farm grid integration Performance

In this thesis, Adama II wind farm operational performance will be analyzed analogs to those requirements of the Ethiopian grid system to sustainably power supply. The main objective of this study is to examine Adama II wind farm grid integration performance. The study investigates the performance through variation of weed speed furthermore the study analyses the downtime and energy production capacity at different wind speed such as at a cut-in speed of 3.5 m/s, at a rated speed of 14.5m/s, and a cut-out speed of 25m/s. The study performs its Modelling and simulation Adama II wind farm using MATLAB and Simulink to analyze its energy production performance and to provide a means to mitigate technical and operational risk by enabling the engineering team to explore design trade-offs, assess control and management system operation, estimate achievable production with confidence, and perform fault studies in a safe and repeatable environment. The wind farm MATLAB and Simulink modeling could be done using two methods one is modeling each wind turbine individually represented and dynamic modeling which is the aggregation method. Increased levels of penetration, place an increased emphasis on scrutinizing the impact that wind power connection has on grid reliability and stability. Adama II wind farm is a large wind power system; hence it requires large models to fully realize the benefit of simulation and performance. However, the development phase of a large-scale simulation model can be the most time-consuming and onerous task. This study chose the former method and represents 102 turbine models with 8 subsystems each containing a model reference 7(WF1, WF2, WF3, WF4, WF5, WF6, and WF7) subsystems have 13 different turbines with different electrical parameters and a DFIG control model and WF8 subsystem do have 11 turbine references and also have a voltage support device at a point of connection to help reactive power system to provide and maintain stability during the simulation as shown below Figure 3.0.6.

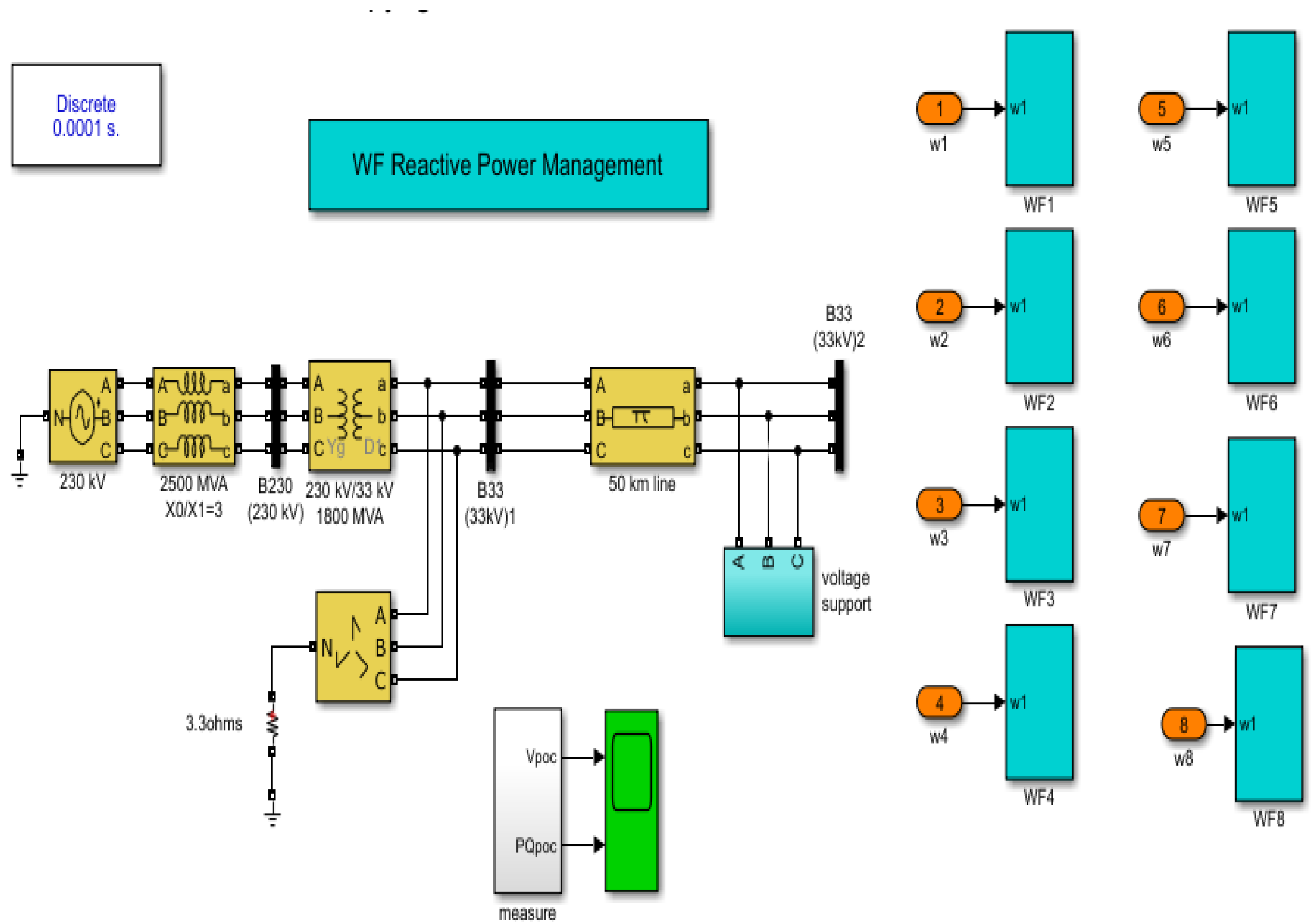


Figure 3.0.6: Adama II wind farm MATLAB SIMULINK model

The model has been developed using Simscape Electrical- Specialized power systems which contain 102 Type III DFIGs wind turbines. Turbines are integrated using Model reference and a simple voltage transfer mechanism in Simulink.

3.3.2 ADAMA II Wind Farm Energy Production Performance

Wind farms that are connected to the EEP grid have to consent to the grid requirements of EEP, which help EEP to have a stable and reliable power system and serve its customers with quality power supply systems. Due to this Adama II Wind farm energy generation should maintain its operating frequency and voltage, at the point of common coupling (PCC), within a range around the rated values.

Analyzing and investigating Adama II wind farm energy production potential is performed starting from wind power calculation and transformation for a wind farm. The function of wind turbines is to transform the wind energy (input) exerted on the impeller into electric power output. wind power transformation power characteristics are below described accordingly.

i) Standard Wind Power Transformation

The standard wind power transformation of the wind turbine is provided by the turbine manufacturers based on the standards of the wind turbine power characteristics. Standards stipulate that under the condition of the standard air density (1.225 kg/m^3).

Table 3.0.3: Adama II wind farm generator manufacturer SE7715 technical specification[26]

Gearbox	Type	DFIG
Operational data	Drive	Direct Drive
	Wind class -IEC	II A
	Rated output voltage	0.69kv
	Rated power	1.5MW
	Frequency	50hz
	Power factor	≥ 0.98
	Cut-in wind speed	3.5m/s
	Rated wind speed	14.5m/s
	Cut-out wind speed	25m/s

	Maximum wind speed(10mins)	42.5m/s
	Blade length	37m
	Operational temperature range	-20ºc-40ºc
	Humidity	5%-95%
	Converter	Full power IGBT converter
	Rated power current	1540kw
Generator	Stator rated current	1110A
	Rotor rated current	489A
Rotor	Diameter	77.7m
Tower	Height	70m

The power extraction of the rotor, calculating the mechanical torque as a function of the airflow on the blades represents as follows;

$$P_T = 1/2\rho\pi R^3 V^2 C_P \quad (3.1)$$

Power coefficient

$$Cp = k_1(\frac{k_2}{\lambda_i} - k_3\beta - k_4\beta^{k_5} - k_6)(e^{\frac{k_7}{\lambda_i}}) \quad (3.2).$$

Tip step ratio

$$\lambda_i = \frac{1}{\lambda + k_8} \quad (3.3)$$

Adama II wind farm is using a variable-speed Doubly-Fed Induction Generator (DFIG), which is a wound rotor induction generator with slip rings, its stator is directly attached to the grid side, and the rotor is connected interfaced through a back-to-back partial-scale power bridge converter using slip rings and brushes as shown in Figure 3.0.7[97][98].

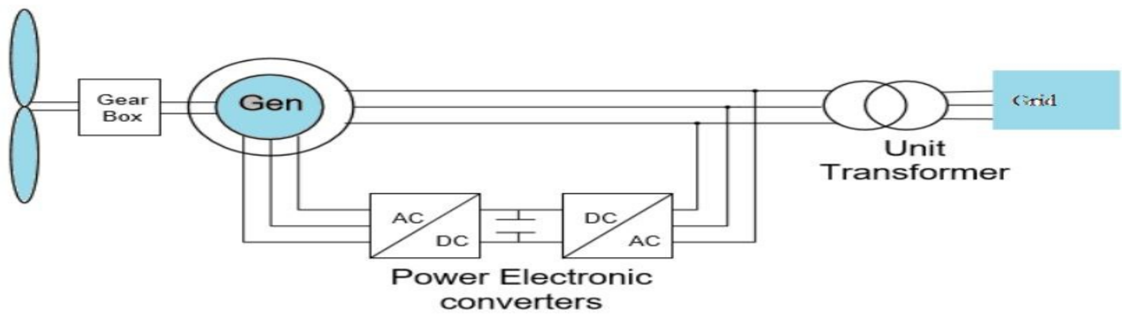


Figure 3.0.7: Schematic diagram of DFIG generator type[34]

Its converter comprises a rotor-side converter and a lineside converter and a common DC bus. the voltage on the stator is applied from the grid network and the voltage on the rotor is induced by the power converter. The voltage source converter supplies the rotor windings with variable voltage and frequency[99]. Its frequency converter is limited to operating at 30% of the generator power so it is more suitable than the one with a full converter for high-power wind turbines[100]. Moreover, it provides quick control of current within limits, and holds the electrical power constant despite the fluctuating wind, thus temporarily storing the fast fluctuations in power as kinetic energy. These characteristics provide reactive power control plus plausibility to design the converter with modest size, and subsequently, lower cost and lower power electronic losses [34].

Table 3.0.4: Adama II wind farm DFIG data[26]

	Parameter	**Value**
DFIG data	Sn	1.6 MVA
	Qmax (Qmin)	0.9(-0.8) MVAr
	Z source	0+j0.8 pu.
	Pmax (Pmin)	1.5(0.0) MW
	M base	1.6MVA
WT transformer data	Sn	1.6MVA
	Unp/Uns	0.69/33KV/KV
	Ztr	0.0012+j0.0057 p.u

	M base	1.6MVA
Substation transformer data	Sn	90 MVA
	Unp/Uns	33/230 KV/KV
	Ztr	0.00361+j0.129950 p.u
	Ytr	0.0005-j0. 00149p.u
	M base	100MVA

ii) Actual Wind Power Transformation of a Wind Turbine

Adama II wind farm installed capacity of the wind farm is 153MW from 102 WT which is grouped into 8 clusters having a 1.5MW capacity each. Each wind turbine generator (WTG) is connected to a 690 V bus, and the WTGs are connected to the wind farm's internal grid through their 0.69/33 kV step-up transformers connected to a 33kV distribution system that exports that power to a 230 kV grid through a 23 km, 33 kV feeder. It's doubly-fed induction generator (DFIG) consists of AC/DC/AC IGBT-based PWM converter. The stator side is interfaced straight to the 50 Hz frequency grid side while the rotor is fed at variable frequency through the AC/DC/AC converter.

Table 3.0.5: Hourly average wind speed and power density measured at 70m height

Hour	1:00	2:00	3:00	4:00	5:00	6:00	7:00	8:00	9:00	10:00	11:00	12:00
Average wind speed(m/s)	9.6	9.6	9.5	9.4	9.2	9.0	8.7	8.1	7.8	8.0	8.2	8.2
Power density(W/m^2)	581.0	572.2	566.0	556.6	521.4	487.9	450.1	365.8	323.6	328.9	335.7	336.1
Hour	13:00	14:00	15:00	16:00	17:00	18:00	19:00	20:00	21:00	22:00	23:00	24:00
Average wind speed(m/s)	8.0	8.0	8.0	8.3	8.5	8.7	9.0	9.4	9.6	9.7	9.7	9.8
Power density(W/m^2)	325.9	323.9	326.6	358.4	389.6	425.6	472.0	549.1	588.8	631.2	629.8	629.1

Table 3.0.6: Wind speed at different heights for each anemometer mast

Month		Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Avg
Adama south area	II	10.2	10.1	11.2	10.5	6.3	7.5	7.9	8.2	6.99	5.71	8.14	8.97	8.48
Adama North area	II	11.4	11.2	10.8	10.8	6.6	7.8	7.4	8.0	6.64	5.27	9.8	10.31	8.83

Table 3.0.7: Turbine Power and Trust coefficient[30]

Wind speed(m/s)	**Power (kW)**	**Trust coefficient**	**Wind speed(m/s)**	**Power (kW)**	**Trust coefficient**
3.5	27.55	0.9375	15	1500.05	0.254
4	50.97	0.8738	16	1500.05	0.2072
5	101.83	0.7631	17	1500.05	0.1721
6	199.87	0.7517	18	1500.05	0.145
7	312.31	0.7515	19	1500.05	0.1237
8	481.46	0.7599	20	1500.05	0.1067
9	695.94	0.7133	21	1500.05	0.093
10	929.75	0.656	22	1500.05	0.0816
11	1129.55	0.5821	23	1500.05	0.0722
12	1311.99	0.5075	24	1500.05	0.0643
13	1451.95	0.4416	25	1500.05	0.0576
14	1500.05	0.3196			

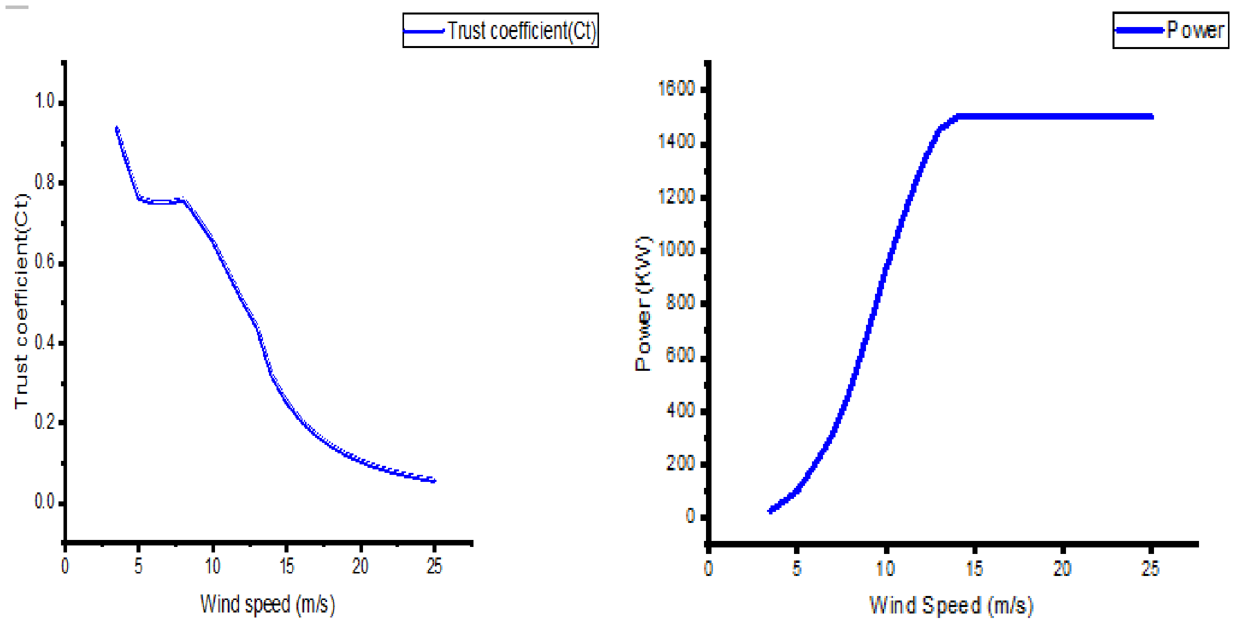


Figure 3.0.8: Power and Trust coefficient

The wind turbines are connected through 33kV underground cables and overhead transmission lines of 50m lengths and capacities depending on the location of each unit and the distance to the 33 kV collector bus. The main substation has two transformers with a total capacity of 180 MVA and with a voltage level of 33/230 kV. The 230kV voltage terminal side is connected to the Koka substation.

$$P^{real}i(t) = f^{real}(vi(t)) \tag{3.4}$$

3.3.3 ADAMA II Wind Power Plant Grid Integration Issues and Analyses

Variable renewable energy grid integration is currently an issue as wind power penetration levels remain expanded in various nations. Such as nations like Ethiopia is an issue that may impede the widespread deployment of the wind farm. The Adama II wind farm has 102 turbines, each turbine is attached to a unit transformer that steps up the generator voltage (690 V) and 1.6MVA into a medium voltage level of 33 kV and all are grouped into eight clusters (clusters A to cluster H). One of the clusters that have eleven turbines, while the remaining seven clusters have thirteen turbines each, grouped and a 33 kV underground line 50meter length connects each cluster to the main substation. The main substation has two transformers with a capacity of 90 MVA (180MVA) with a voltage level of 230/33 kV. It has two shunt reactors BKSMC-30000KVAr each. The high voltage terminal side is connected to the Koka substation with a single 230 kV overhead transmission line.

In this thesis Adama II wind farm fault ride-through analysis, short circuit analysis, speed variation, and control fault impact on EEP grid power system impact analysis is carried out based on EEP grid integration requirement.

3.3.3.1 Fault Ride-Through Analysis

A challenge for a weak grid system is low response during fault recovery, unable control active power(P) and reactive power(Q), complex control can interact with the transmission system with negative impact, and proper tunning is necessary, especially in weak grid systems.

During the recovery period, once the fault is detected the operator will reduce injecting active power into the grid, and the detected fault once cleared and the voltage recovered to a certain level then start injecting the active power slowly till reaching its rated power value. Adama II wind farm helps this recovery by injecting a little bit more reactive power during this recovery period. Generally, during the fault recovering period Adama II wind farm is conducting decreasing active power and increase reactive power. This requirement does meet through the controller of the converter obesely using controlling the current injected into the rotor by measuring the phase voltage.

Wind farm and collector system connected to the power grid network Breakers opened due to a fault on AC network Breaker isolates wind turbines and the cables from the grid Rapid increase of a collector network and terminal voltage of WTs Simulations result shows assume the fault is for a short time, the three-phase fault was applied at 1s and the circuit breakers on the faulted line opened at 1.2 s and reclosed at 2 s. The results for both cases show the active power and the rotor speed of the DFIG, while the pitch angle, the DC-link voltage, and the rotor power of the DFIG are shown in the reactive power of the GSC, the terminal voltage, and the turbine torque is displayed, respectively. It can be observed that the DFIG variables were able to assume their normal state after the grid fault because the DFIG system can provide reactive power to stabilize itself to its steady state after the fault. The DFIG system is more stable during grid fault in the power system compared to the IG wind turbines, because it can provide sufficient reactive power to stabilize itself during grid fault via its power converters.

During normal operation, the controller gives the priority to the active current the wind turbines are equipped to fulfill the grid code requirements regarding voltage support. The FRT function is activated when the voltage deviation is above a user-defined threshold value and deactivated when the deviation goes back below another seated threshold value. FRT function is active for LVRT pr HVRT on the rotor side controller gives the priority to the reactive current. Similar to the rotor side converter the property is given to the grid side converter reactive current when the FRT function is activated to improve the high voltage ride through an FRT capability of the DFIG generator wind turbine reactive current contribution of the grid side converter is also used the grid side converter reactive current contribution is achieved by LVRT boost and HVRT boost blocks during low voltage and high voltage conditions. During LVRT the grid side converter does not contribute before the maximum rotor side contribution is reached then it's not contributing with a proportional controller the HVRT also over voltage ride through is activated when the voltage goes above a certain threshold value[101].

3.3.3.2 Rapid Wind Speed Variation Impact

The analysis of data available from operating wind farms and meteorological measurements at typical wind farm locations allows us to quantify the variations in net wind power output that can be expected for a given period. The distinction between these specific timescales is made since this type of information corresponds to the various types of power plants for balancing. The results from analyses show that the power system can handle this variability well. System operators only need to deal with the net output of large groups of wind farms, and the wind power variability is viewed as the level and variation in power demand. Variations within the Minute The fast variations (seconds to a minute) of aggregated wind power output (as a consequence of turbulence or transient events) are quite small, due to the aggregation of wind turbines and wind farms, and hardly impact the system.[102] Variations within the Hour The variations within an hour are much more significant for the system.

The wind speed variation causes the APV to change through the variation in active power. The active power of the DFIG increases with the increase in wind speed, thereby resulting in a decrease in voltage. Similarly, the decrease in wind speed causes an increase in voltage.

3.3.3.3 Active Power and Reactive Power Control

Production and absorption of reactive power at the wind farm may arise depending on the excitation, and when the generator is over-excited it generates reactive power, and when the generator is under excitement it absorbs reactive power.

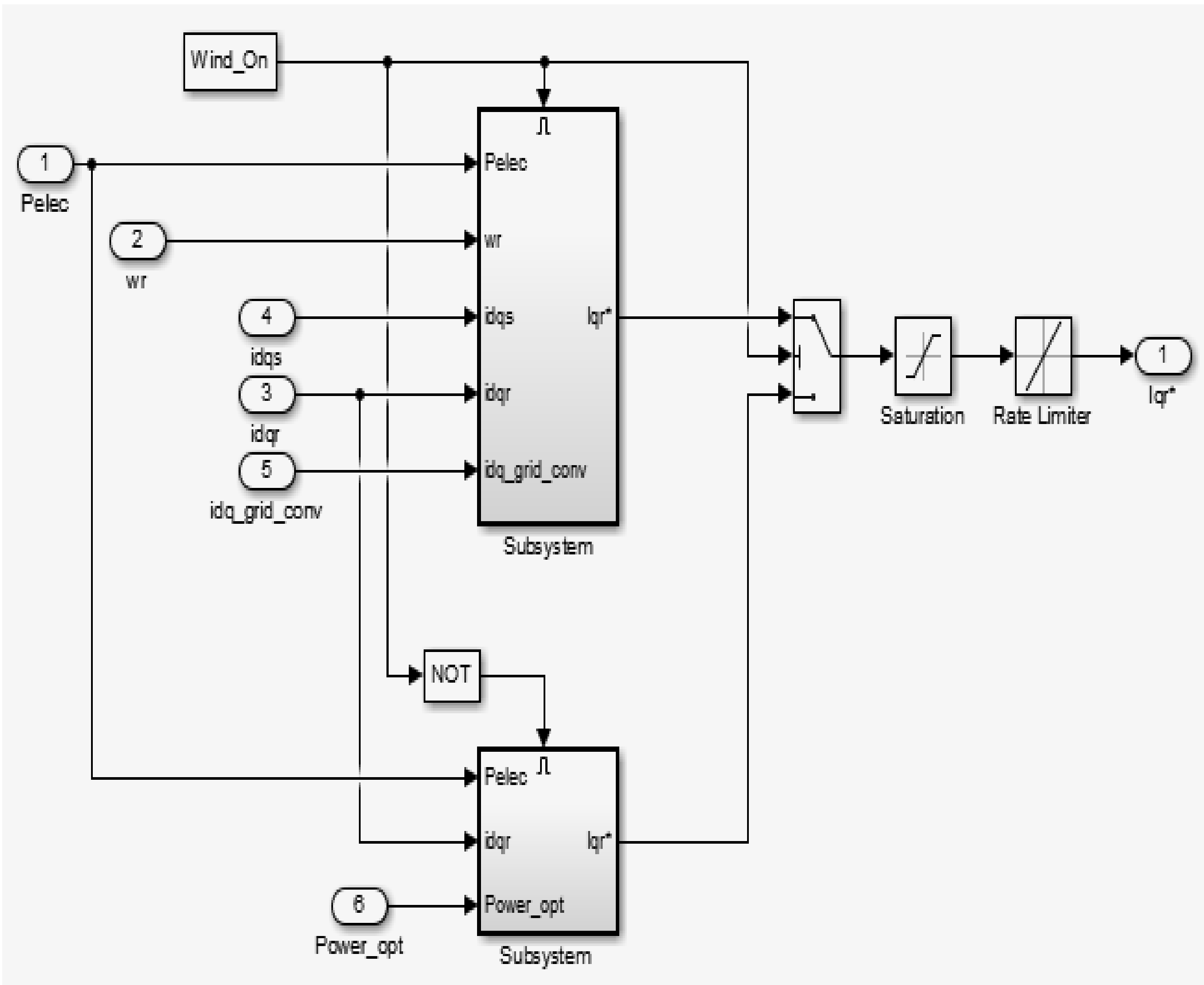


Figure 3.0.9: Active power control

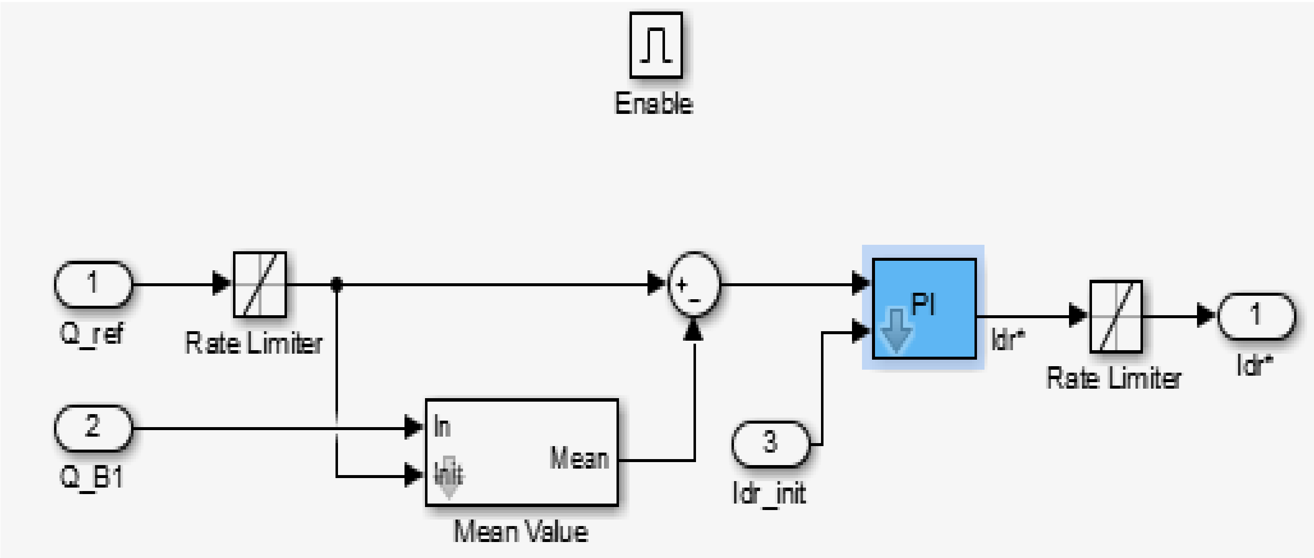


Figure 3.0.10: Reactive power controller

To regulate active and reactive powers injected at the point of common coupling, as shown in Figure 3.0.9 and Figure 3.0.10 controller model controls the flow of signals between different subsystems.

The control system performs the following tasks for active power:

i. Evaluate the operation mode for active power control: receive a reference or deliver all available power, automatic frequency control, delta, or balance control.
ii. Limit the generation deviation if necessary (power gradient limiter).
iii. Regulate the active power in the PCC.

Dispatch the wind turbine active power reference (P_{ref}^{WTi}) as a function of the wind farm power reference (P_{ref}^{WF}). The dispatch function can be done, as a function of the available power (P_{disp}^{WTi}) of each wind turbine:

$$\boldsymbol{P_{ref}^{WTi}}=\frac{\boldsymbol{P_{dsip}^{WTi}}}{\boldsymbol{P_{disp}^{WF}}}\,\boldsymbol{P_{ref}^{WTi}} \qquad \mathbf{3.5}$$

$$\boldsymbol{P_{disp}^{WF}}=\sum_{i=0}^{n}\boldsymbol{P_{disp}^{WTi}} \qquad \mathbf{3.6}$$

The control system performs the following tasks for reactive power:

- Evaluate the operation mode for reactive power control: receive a reference or deliver all available power, automatic voltage control, and reactive control.
- Regulate the reactive power in the PCC.
- Dispatch the wind turbine power reference Q_{ref}^{WTi} as a function of the wind farm power reference Q_{ref}^{WF}.The dispatch function can be done as a function of the available power Q_{disp}^{WF} of each wind turbine:

$$Q_{ref}^{WTi}=\frac{Q_{dsip}^{WTi}}{Q_{disp}^{WF}}\,Q_{ref}^{WTi} \qquad 3.7$$

$$Q_{disp}^{WF}=\sum_{i=0}^{n} Q_{disp}^{WTi} \qquad 3.8$$

- **Frequency Response**

The balance between generation and load is achieved by frequency control. frequency stability is one of the criteria which have to be always met into keeping the power system stable. If the load exceeds the power supply generation the sinusoidal frequency will slow down and vice versa. Frequency control is performed through the electrical behavior of the network, in terms of frequency and voltage, due to its dynamic nature is continuously changing. Generally, these changes occur in very small quantities. It is a requirement that users of the transmission system can continue operating in a normal manner over a specified range of frequency and voltage conditions. Concerning frequency and for a 50Hz system, this would be in the range of 49 to 51Hz. Concerning voltage, this range could be ±10% of the nominal voltage. However, at times the ranges could be wider, although it would normally be expected that the user would continue operating under an extreme condition for a defined period, for example, 47 Hz for 15 seconds or 20% of the nominal voltage for 1 hour. Beyond these extremes, the user would normally be required to disconnect from the system[103]

Rapid power adjustment of the DFIG is an effective method to solve the voltage problem caused by the active power variation in a wind power system. The required reactive power change constantly because of the wind speed variation. Meanwhile, the feasible power ranges of the DFIG change with the wind speed variation because the rotor excitation is affected by the RSC control. The reactive power demanded by the system and limited by the DFIG under the wind speed variation is determined. Then, an emergency reactive power control method of the DFIG is presented to instantly prevent the voltage change caused by wind speed variation. The dynamic processes of the control condition. Thus, the reactive power capability of the DFIG can be fully exploited and the voltage can be rapidly stabilized in a certain range. The method possesses the advantages of high efficiency, simplicity, and a small effect on the DFIG[104]. The wind turbine contains a high-speed and a low-speed shaft, connected through a gearbox (where the low-speed shaft is attached to the rotor hub and the high-speed shaft is attached to the generator).

In this study, the wind speed is seat to vary from 3.5m/s, 8m/s, 11m/s, 14.5 m/s, and above rated value. From the starting point, wind speed is stated at a rated value of 14.5m/s, then at t = 5s, wind speed increases suddenly to 11 m/s. then analyze the wind turbine voltage, current, generated active and reactive powers values, DC bus voltage, and turbine speed. At normal rated operation the wind farm generates 153 MW then the turbine speed is seated at 1.2 pu of generator synchronous speed. At t = 5 s, the generated active power starts increasing smoothly (together with the turbine speed) to decrease from its rated value in approximately 15 s. Over that time frame, the turbine speed will have increased from 1.2 pu to 0.8 pu.

At normal rated operation the wind farm generates 153 MW then the turbine speed is seated at 1.2 pu of generator synchronous speed. The DC voltage is regulated at 1150 V and reactive power is kept at 0 Mvar. At t=0.03 s the positive-sequence voltage suddenly drops to 0.5 p.u. causing an oscillation in the DC bus voltage and the DFIG output power. During the voltage sag, the control system tries to regulate DC voltage and reactive power at their set points (1150 V, 0 Mvar). The system recovers in approximately 4 cycles. The power output and the Cp values are used in Table 3.0.7 data. For a rated wind speed of 14.5 m/s, the turbine output power is 1 pu of its rated power, the pitch angle is 8.7 deg and the generator speed is 1.2 pu.

3.3.3.4 Short Circuit Fault Analysis

DFIG WT at a stator side of synchronous generator directly connected to the grid. The wind turbine with DFIG uses a frequency converter and a pitch blade actuator to control directly the generator speed and wind turbine output. The frequency converter has a rotor-side converter (RSC) and a grid-side converter (GSC). The frequency rotor side converter independently controls active and reactive power, while its grid side converter also controls the active power flow through the converter by controlling the DC-link voltage to unity[105].

To analyze Adama II wind farm performance, applied a three-phase short circuit fault very close to the point of common coupling (PCC) at zero seconds and will be cleared after a hundred milliseconds. This will cause the voltage at that point to fall to zero. The turbines in the wind farm are configured to inject additional reactive current into the network to support voltage in the event of such a fault. This carried out a dynamic simulation to demonstrate this behavior a 0.15 pu voltage drop lasting 0.5 s is programmed to occur at t = 5 s. seat control mode in Var regulation with Qref = 0.

3.3.3.5 Control Faults Analysis

Wind Farm Control System defines the requirements for each wind turbine and the substation reactive power static compensation (capacitor banks or inductors) in real-time. The inputs will be the system operator references, measurements from the point of common coupling (PCC), and the state and available power of each wind turbine. The control objective of the wind farm control is to evaluate the operation mode for active power control: receive a reference or deliver all available power, automatic frequency control, delta or balance control, Limit the generation deviation, if necessary (power gradient limiter), Regulate the active power in the PCC and Dispatch the wind turbine active power reference as a function of the wind farm power reference.[106]

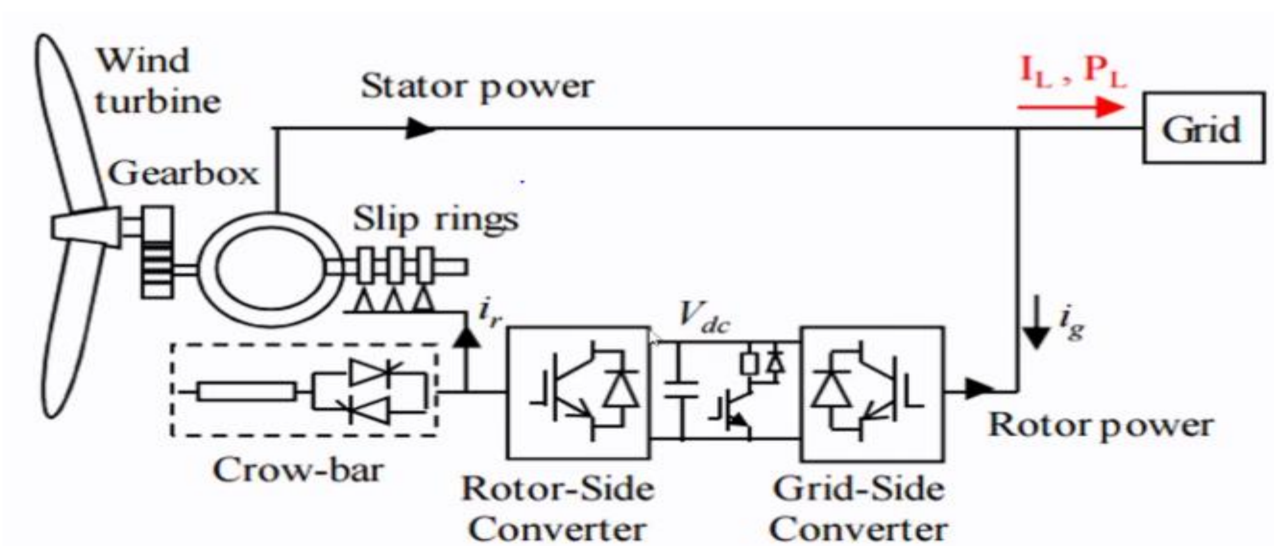


Figure 3.0.11: DFIG WT controller schematic diagram[104]

Adama II wind farms DFIG wind turbines converter system consists of two voltage source converters namely a grid side converter and a rotor side converter. Furthermore, a line inductor which is a choke filter, and a shunt harmonic AC filter are used on the grid side converter to improve the power quality of the farm a crowbar is used to protect the rotor side converter against over current and DC capacitor against over voltage. During crowbar ignition, the rotor side converter is blocked and the induction generator consumes reactive power to avoid the crowbar ignition during faults the DC resistive chopper is widely used to limit the DC voltage.

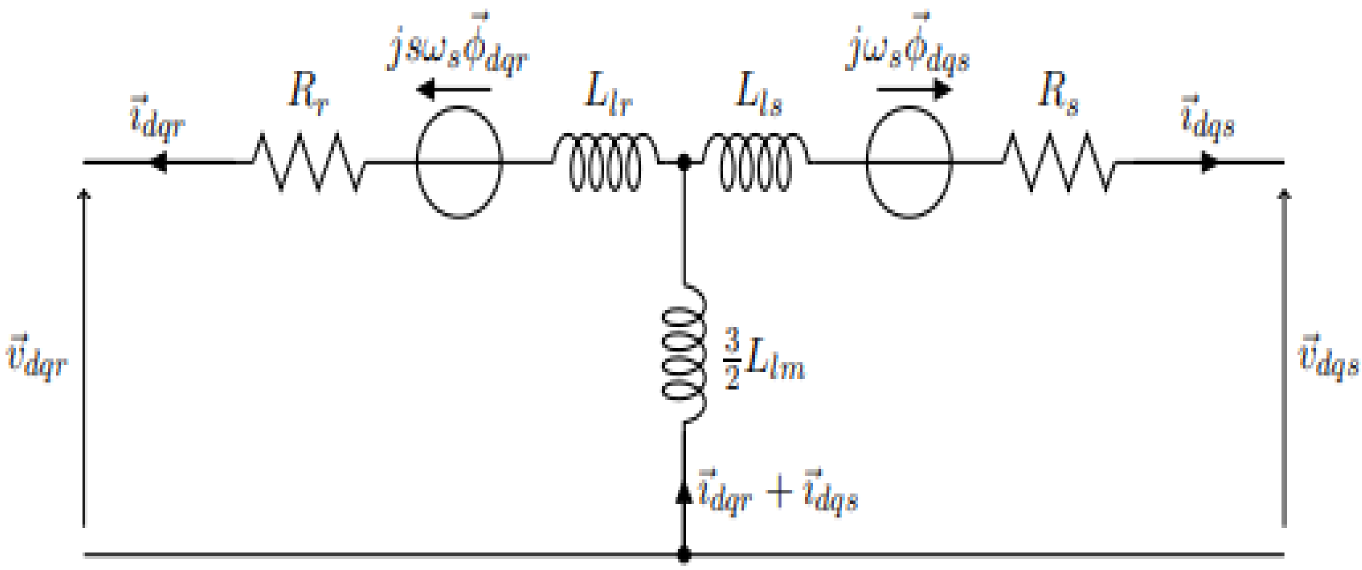


Figure 3.0.12: DFIG equivalent circuit[99]

i. Rotor Side Converter (RSC)

In normal operation, the RSC controls the developed electric power (*Pg*) and the absorbed reactive power by the DFIG. $\theta r$is obtained from the phase lock loop (PLL) angle θ and the generator rotor position is the effective angle for the ABC-dq0 and the dq0-qbc transformations. The direct axis component is used to regulate the generator power factor to 1.0 pu (per unit); thus, the absorbed reactive power reference (*Q**) is equal to zero. The actual absorbed reactive power at the grid connection (*Qg*) of the DFIG is compared to the reference and the error is sent to the first proportion (PI) controller to determine the reference current *idr* for the direct axis component. Then, *it* is compared to the actual value of *id* and the error is sent to the second Pl controller to determine the reference voltage *Vqr** for the direct axis component.

The quadrature axis component is controlled similarly to the direct axis; however, it regulates the electric power to the optimal reference $P_{op}t^*$. After a dq0-to-ABC transformation, *Vdr** and *Vqr** are sent to the pulse width modulation (PWM) signal generator. Finally, *Vabc** are the three-phase voltages desired at the rotor side converter output for switching the IGBTs.

ii. Grid Side Converter (GSC)

For the grid-side converter, the gain of the d-axis inner loop depends on the total impedance seen by the converter. The transfer function is shown here where R and L are the resistances and inductances of the filter choke the converter transformer the farm transformer and the grid side non-impedance combined set the rise time which determines the inner loop speed which is seated to 10millisecond. The voltage control is at the converter terminal but the voltage measured is after the choke filter therefore and similarly to the machine side converter fit for what compensation is done before putting the converter voltage reference back to the ABC domain.

$$G(s) = \frac{1}{R + sL} \tag{3.9}$$

The relationship between the bandwidth and the rise time

$$\alpha c = \frac{ln(9)}{T_{rise}} \tag{3.10}$$

To analyze the impact of Adama II wind farm control system fault on grid and plant performance, apply fault on rotor side controller system. First, in the wind speed step block, disable the wind speed step by changing the Final value from 14 to 8 m/s. in the control source menu. Fault in IGBT in the open state and lasting 0.5 s is programmed to occur at t = 5 s. seat control mode in Var regulation with $Q_{ref} = 0$.

3.4 Wind Power Production Long-Term Forecasting Using Machine Learning Method

Several energy prediction models employ a diversity of high-level approaches to transform the data usage into prevailing long-term, medium-term, and short-term prediction algorithms. The study primarily steps to work through a year head forecasting modeling in machine learning with Python programming language in anaconda framework, starts mapping Python 3.9 version and load required libraries onto this process i.e., setup Pandas for data loading and TensorFlow for modeling.

The goal of the thesis is to present long-term wind power forecasting which would improve Adama II wind farm grid integration performance by providing a solution for reliable maintenance scheduling, reliable plant operation, and safely integrating of Adama II wind power plant into the national grid. hence the study will consider two factors in evaluating the Adama II wind power plant, one is power as the dependent variable and the independent variables are wind speed and outdoor temperature.

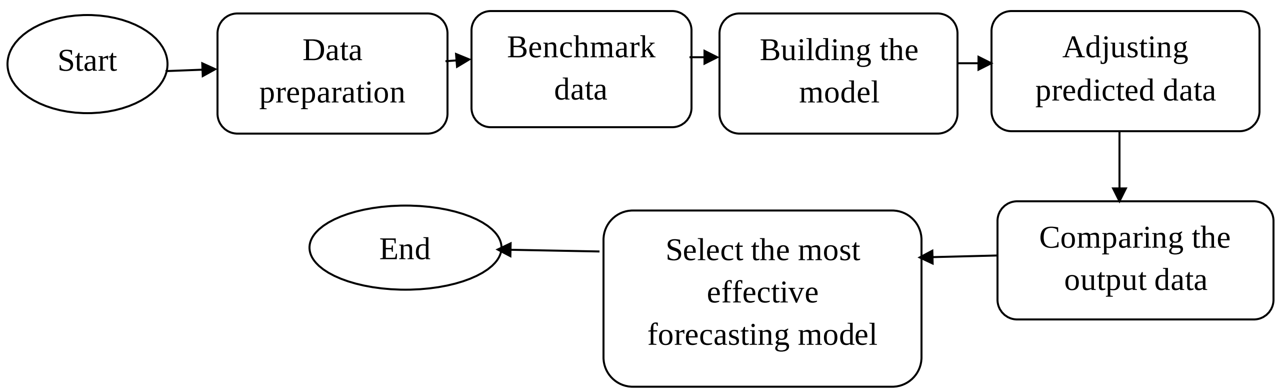


Figure 3.0.13: Adama II wind farm power production forecasting method

This Long-term forecasting model developing objective method starts with original data collection from SCADA, data processing, high-dimensional data feature analysis, model formalization based on SARIMAX and XGBoost machine learning, model structure optimization, and finally, validation and test model performance.

3.4.1 Adding Features to Data

Feature extraction refers to processes that reduce the dimensionality of the initial raw data set to more manageable groups for processing [33]. Large data sets require a lot of computational resources to process, therefore, selecting appropriate and/or combining features can help reduce the computational requirements. For forecasting-based models, this reduction can lead to accuracy improvement, overfitting risk reductions, and decreased computational resources. Adding weekdays, month, day of the month, hour of the day, year, and season as extra columns. Mapping the weekdays to use the actual weekdays in words like 'Monday', etc. Python usually indicates Monday as 0, Tuesday as 1, and so on. Adding season based on the data as shown in Table 3.0.8

Table 3.0.8: Feature added data

	Dates	Wind Speed	Power	Outdoor Temperature	Date	year	month	day	hour	weekday	season
0	2016-01-01 00:00:00	14.7	1518.7	17.8	2016-01-01	2016	1	1	0	Friday	winter
1	2016-01-01 01:00:00	12.7	1480.6	17.7	2016-01-01	2016	1	1	1	Friday	winter
2	2016-01-01 02:00:00	6.8	298.0	16.8	2016-01-01	2016	1	1	2	Friday	winter
3	2016-01-01 03:00:00	8.2	548.9	15.9	2016-01-01	2016	1	1	3	Friday	winter
4	2016-01-01 04:00:00	8.3	552.2	15.1	2016-01-01	2016	1	1	4	Friday	winter
5	2016-01-01 05:00:00	8.1	535.8	14.7	2016-01-01	2016	1	1	5	Friday	winter
6	2016-01-01 06:00:00	6.3	251.6	14.7	2016-01-01	2016	1	1	6	Friday	winter
7	2016-01-01 07:00:00	5.6	166.1	14.8	2016-01-01	2016	1	1	7	Friday	winter
8	2016-01-01 08:00:00	5.4	147.8	16.3	2016-01-01	2016	1	1	8	Friday	winter
9	2016-01-01 09:00:00	5.5	153.0	18.7	2016-01-01	2016	1	1	9	Friday	winter
10	2016-01-01 10:00:00	6.3	247.1	20.1	2016-01-01	2016	1	1	10	Friday	winter
11	2016-01-01 11:00:00	6.9	311.7	21.3	2016-01-01	2016	1	1	11	Friday	winter
12	2016-01-01 12:00:00	7.0	311.1	21.3	2016-01-01	2016	1	1	12	Friday	winter
13	2016-01-01 13:00:00	5.5	157.6	22.6	2016-01-01	2016	1	1	13	Friday	winter
14	2016-01-01 14:00:00	5.9	199.6	23.4	2016-01-01	2016	1	1	14	Friday	winter
15	2016-01-01 15:00:00	3.0	0.0	24.8	2016-01-01	2016	1	1	15	Friday	winter

3.4.2 Data Wrangling, Exploration, and Stats

To get a clear insight of how the power production varies across any particular day averaged over the entire period and also to investigate the effect of weather on the wind power generation we need to plot some graphs. The figure below presents the monthly average power production and average hourly generation profile over the entire period of 2016-2021. From the average hourly power production graph, we can observe how the power remains low over the night and then starts increasing mid-day.

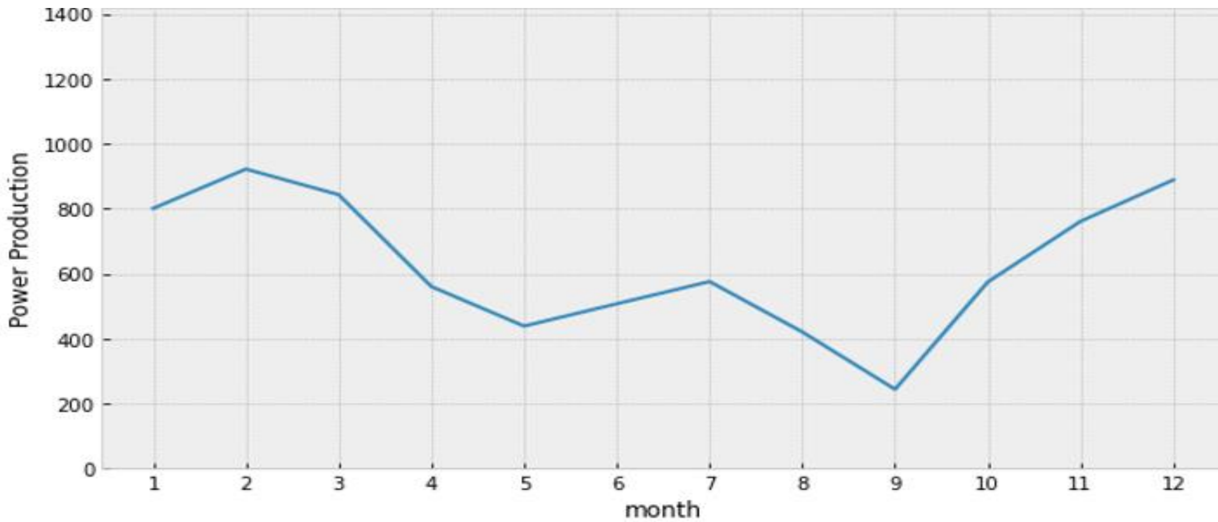


Figure 3.0.14: Power production over 6 years (2016-2021)

Table 3.0.9: Average power production over the years and months

	Month											
Year	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
2016	783.96	1018.63	859.00	405.33	366.49	565.35	507.36	454.05	253.51	635.65	825.52	929.32
2017	783.36	843.39	816.86	531.26	388.74	468.10	556.19	454.05	221.97	546.39	684.91	841.69
2018	783.36	807.68	791.95	464.70	435.56	456.80	547.79	454.05	261.24	555.61	764.26	910.327
2019	784.06	970.70	848.74	716.85	607.58	478.11	574.12	454.05	237.30	543.26	716.47	929.657
2020	783.36	1005.81	660.04	546.18	369.37	519.42	596.57	454.05	609.83	651.88	870.86	900.20
2021	897.16	881.49	1084.95	710.89	480.95	556.64	673.14	454.05	256.97	596.67	870.86	900.20

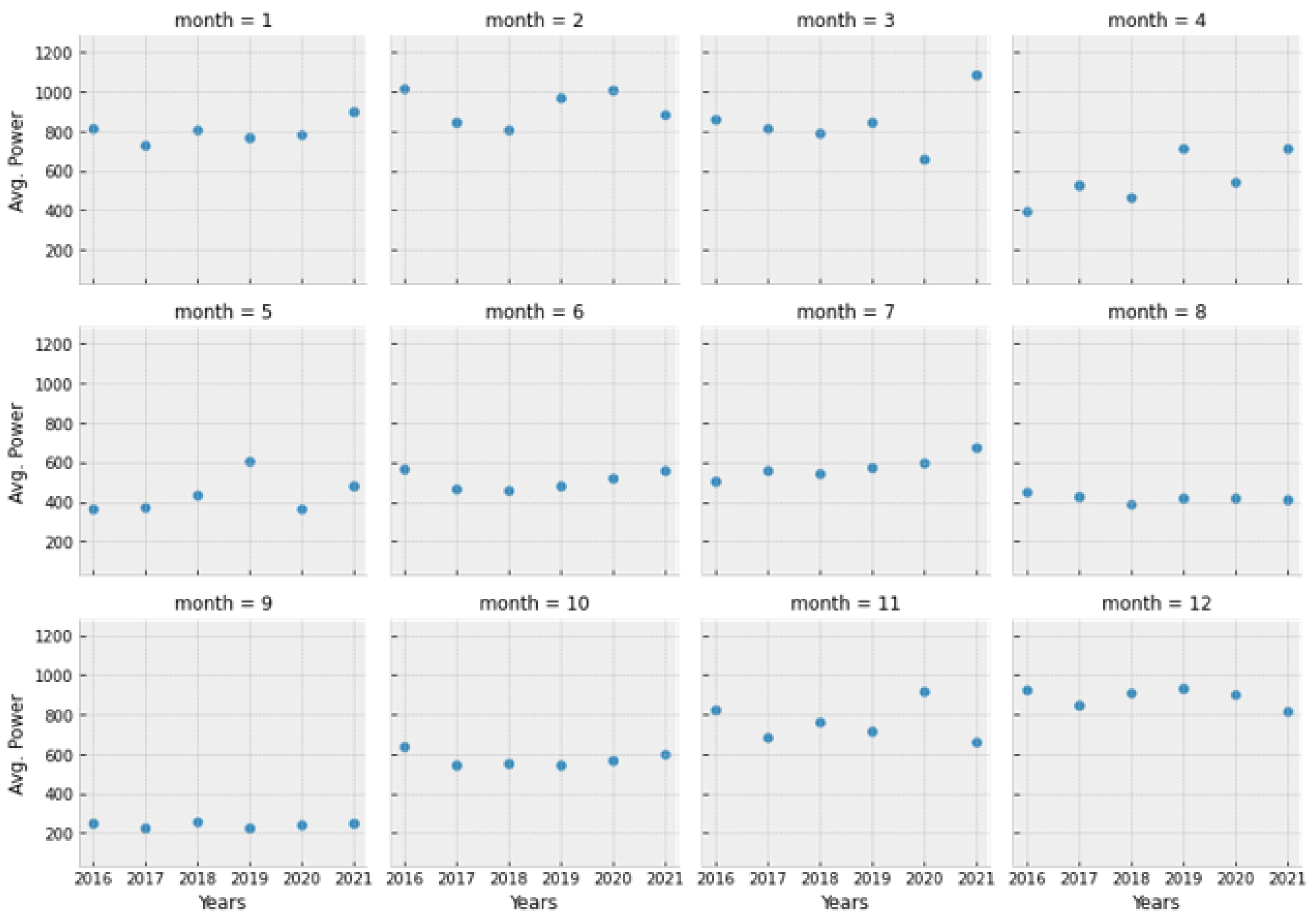


Figure 3.0.15: Power production yearly and monthly variation

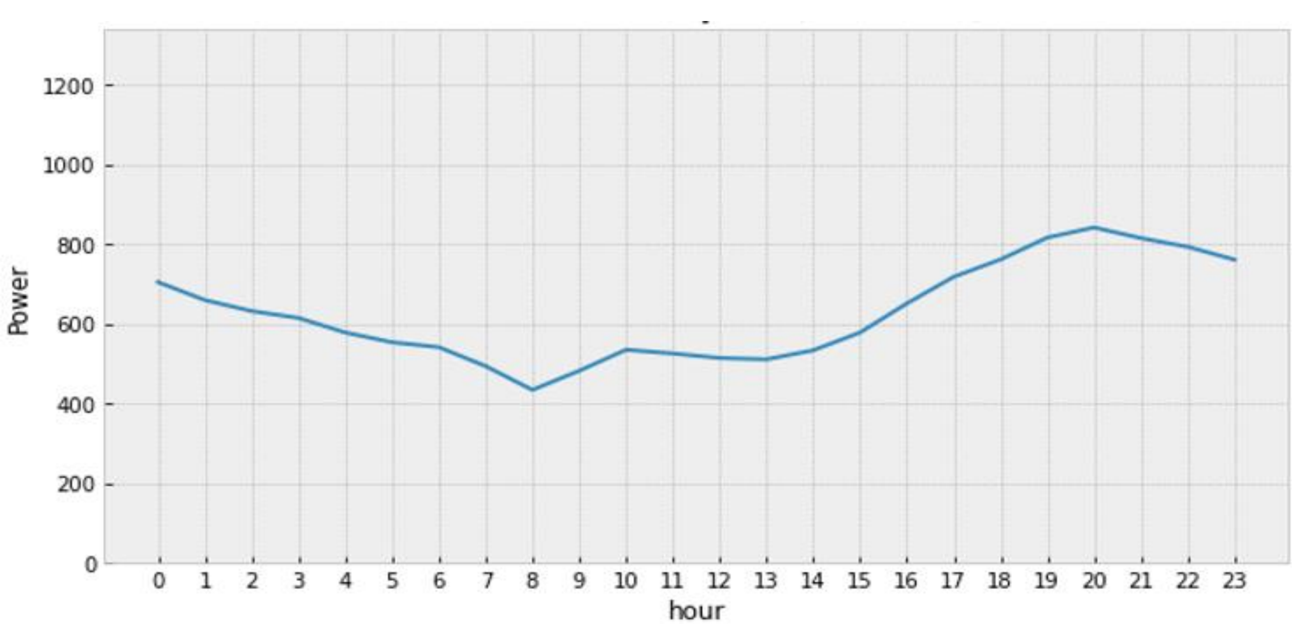


Figure 3.0.16: Power production hourly variation

It can be seen that the average generation capacity during the daytime reaches 1500W and it decreases during the night during night time at a peak (>1500W). Visualizing the distribution of Power Production values for different years.

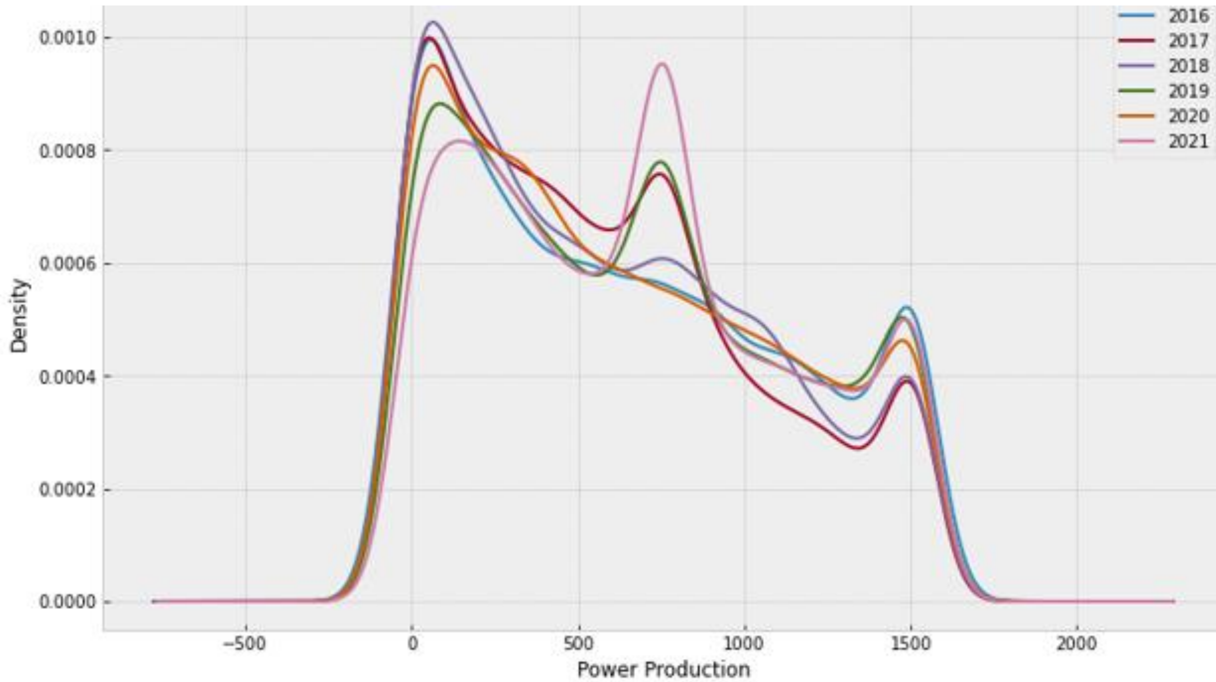


Figure 3.0.17: Variation in power generation over 6 years (2016-21)

The Power production for winter months is more widespread and is more right-skewed towards higher values as compared to summer months for reasons discussed previously. The power generation is bimodal for winter months for all 6 years whereas the power generation is bimodal for summer months for years 2016 and 2017 and starts getting unimodal for years 2016 through 2018. Also, the trend of maximum power generation shifting towards lower values is more dominant in the winter months as compared to the summer months.

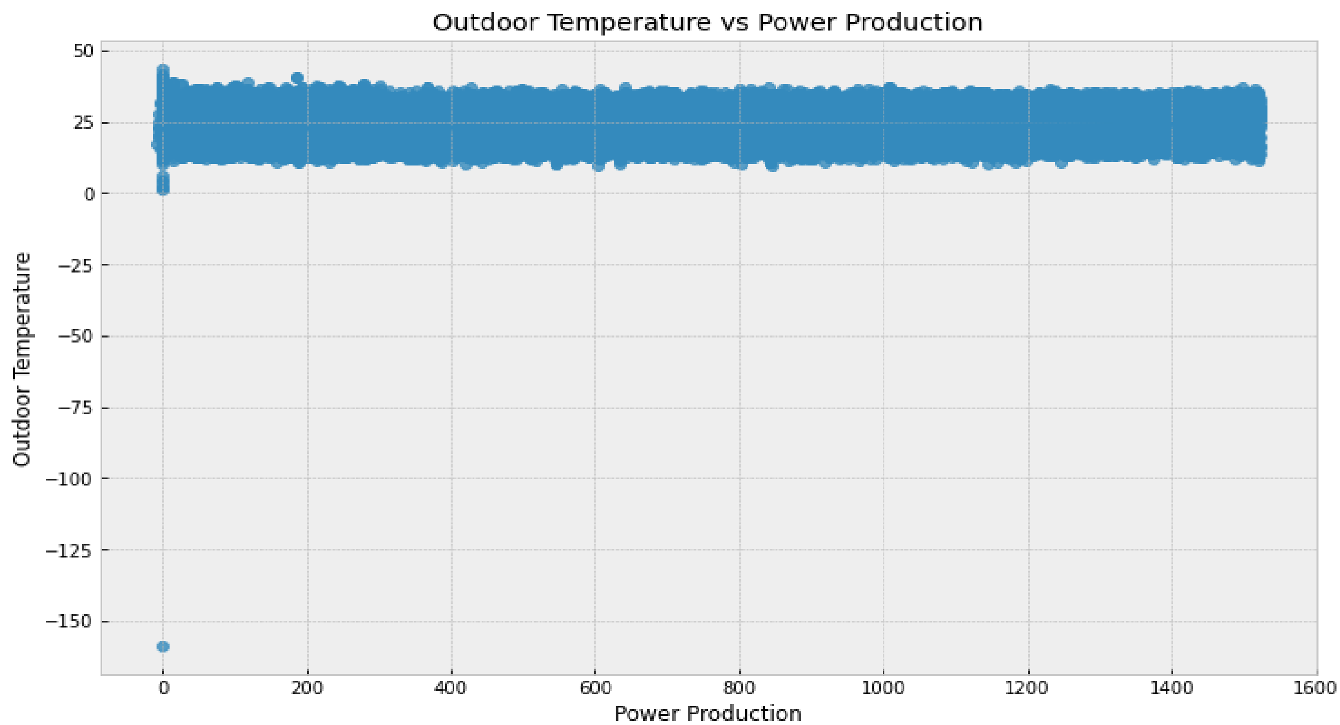


Figure 3.0.18: Outdoor temperature vs Power production

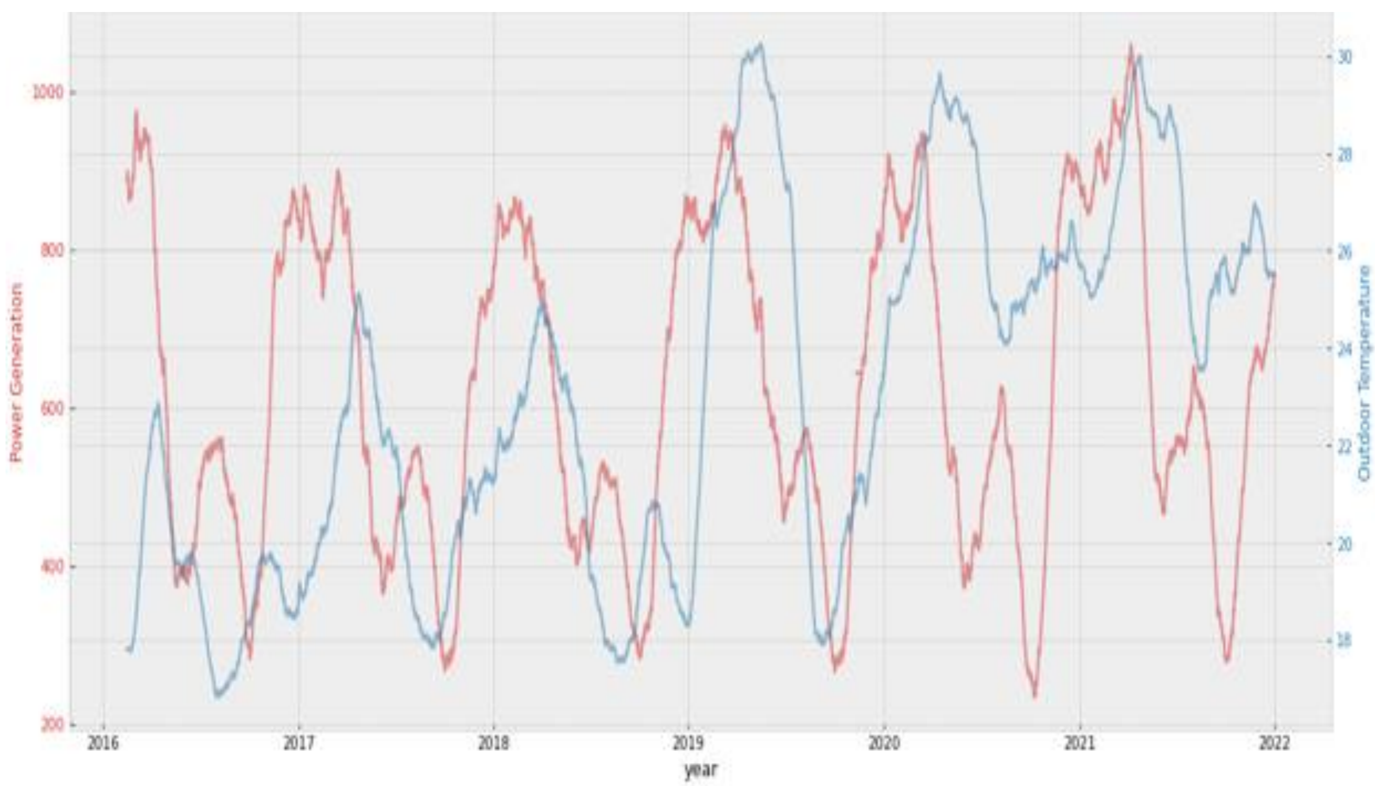


Figure 3.0.19: Power generation and outdoor temperature relation

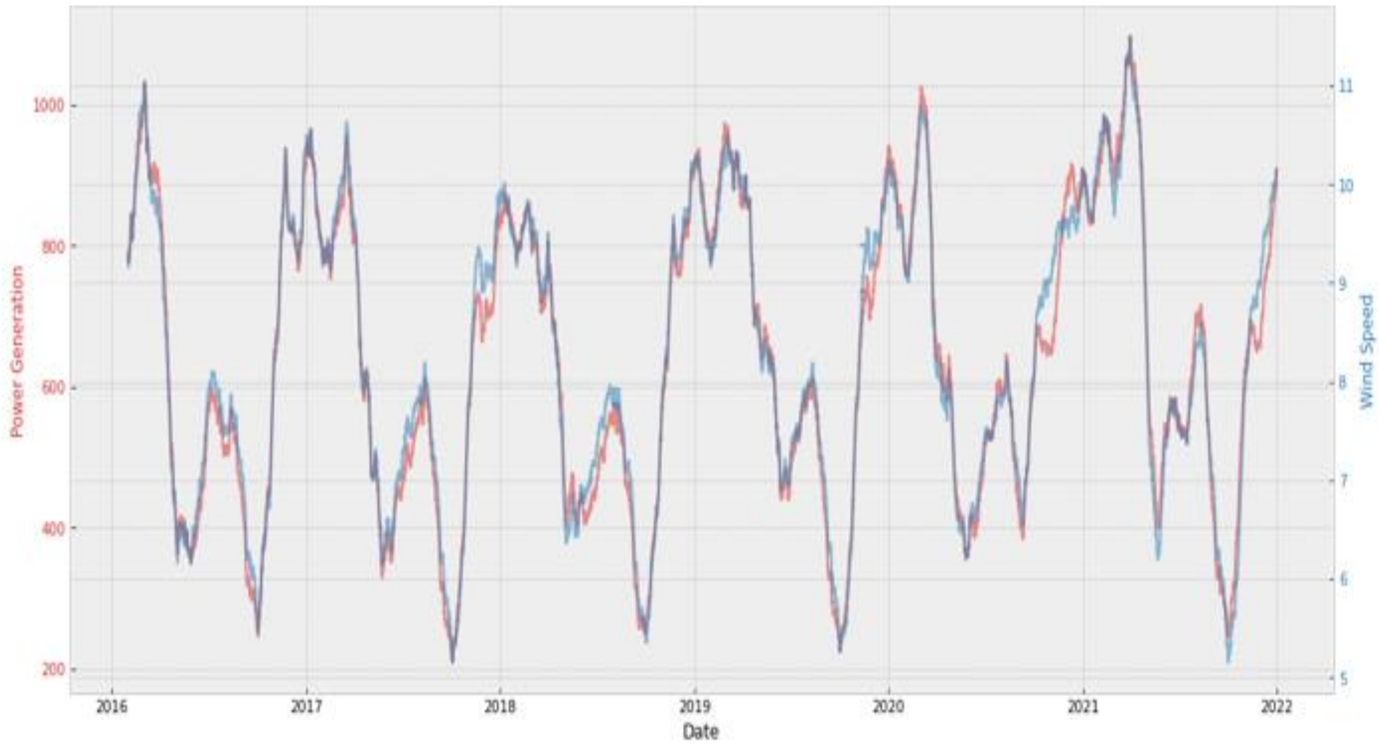


Figure 3.0.20: Wind Speed and Power Generation relation

There seems to be a pretty decent correlation between Power generation and wind Speed. It can also see the correlations using SciPy. stats. pearsonr function. The SciPy. stats. pearsonr function returns the Pearson coefficient and the P-value of observing such coefficient if it assumed that there was no correlation between the x and y data sets. Let's select a significance level of 5%, and so if the p-value is <5%, it will assume that the correlation coefficient returned is significant.

(0.926853565029216, 0.0).

Therefore, the correlation between wind power generation and wind speed is positive and also since the p-value is almost 0, therefore wind speed and power generation are correlated.

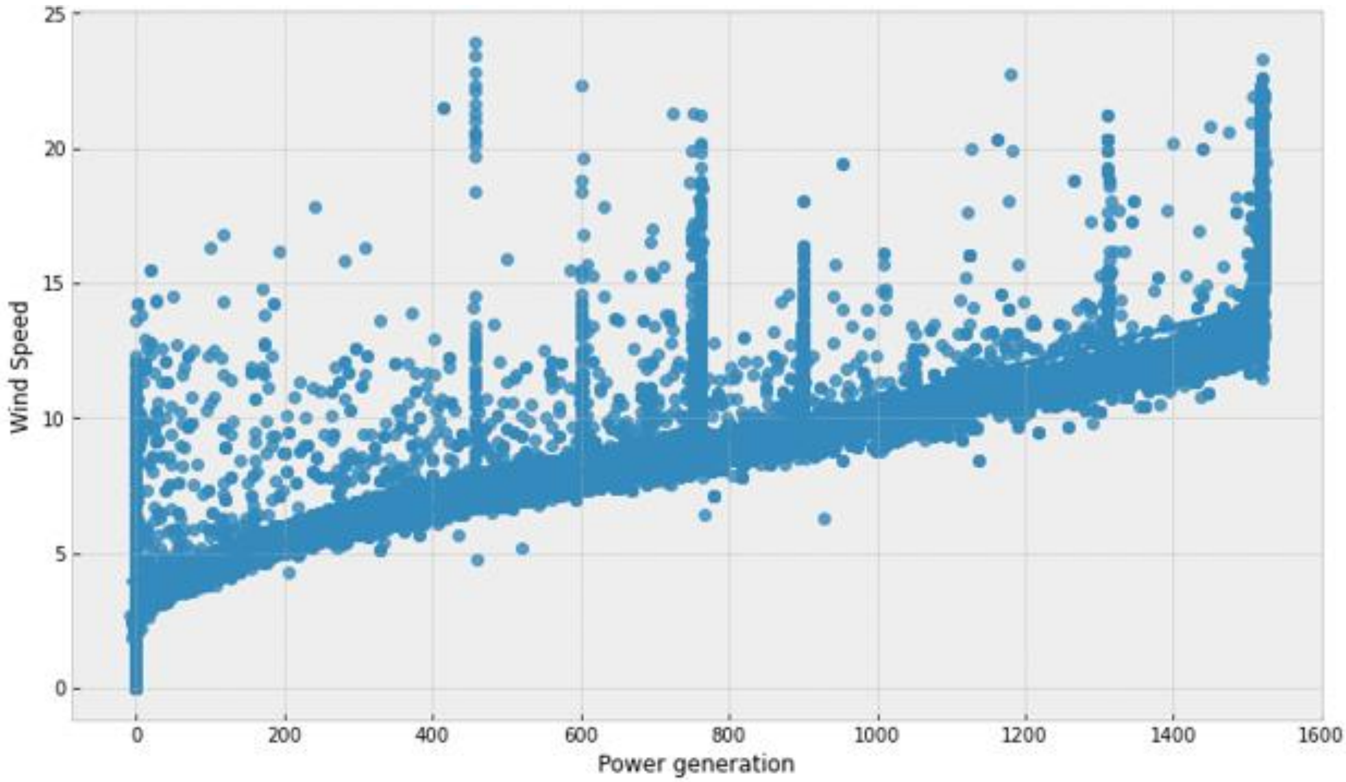


Figure 3.0.21: Wind Speed vs Power Generation

3.4.3 Stationarity Test

Stationarity is having a great influence on forecasting wind farm time series data. To get a good result each point of the data should be independent of one another and the statistical properties of the data should not change over time namely, its mean and variance. The covariance function does not depend on time; it should only depend on the distance between observations. stationarity is important to make predictions on a stationary series since it has assumed that the future statistical properties will not be different from those currently observed. Most of the time-series models, in one way or the other, try to predict those properties (mean or variance, for example). Future predictions would be wrong if the original series were not stationary.

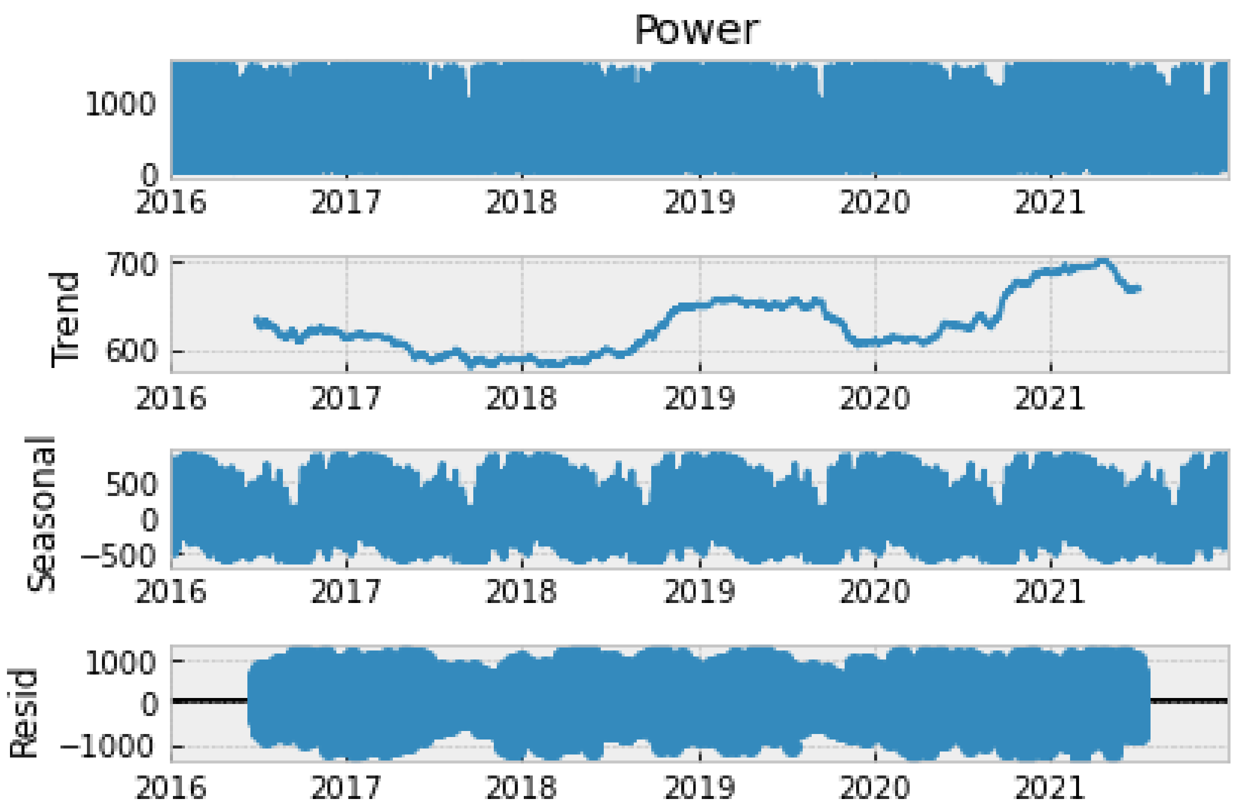


Figure 3.0.22: Power generation stationarity characteristics

The time series forecasting data does important for decomposing the power production dataset, especially when we tell it that data has a periodicity of 24*365 hours. The trend shows how the power production decreases over the years from 2016 to 21 which we had already inferred from the linear regression coefficient values for the year variable from the linear regression models. But, another important thing to keep in mind here is that the trend, though observably clear, is very small. The seasonal component captures the summer and winter trend's good results too. From the above definition of stationarity, it is clear that for wind turbine power production dataset is not stationary because it has a trend (changing mean) and also seasonality which means that the covariance function does depend on time. The simplest way to identify stationarity (or its absence) is viewing the data as it did above by decomposing it but the most common way of testing a dataset for stationarity is the Dicky Fuller test which tests for a unit root. If the p-value of the test is too small (say less than 0.05, giving us 95% confidence) then it has rejected the hypothesis that our data is non-stationary and assume that it is stationary indeed. And the most common way of dealing with stationarity is differencing our dataset.

3.4.4 Exponential Smoothing

Simple techniques like rolling the average of the past values are often useful to visualize the trend in a dataset. The simplest model for a time series will be a persistent model were simply

$yt = yt - 1$. Most of the time series models are compared to this naïve model to test their performance. A more advanced smoothing technique is called exponential smoothing and it is given as:

$$\hat{y}\,t = \alpha \cdot yt + \ (1-\alpha) \cdot \hat{y}\,t - 1y^{t} = \alpha \cdot yt + (1-\alpha) \cdot y^{t} - 1 \qquad (3.11)$$

Here the model value is a weighted average between the current true value and the previous model values. The αα weight is called a smoothing factor. It defines how quickly will "forget" the last available true observation. The smaller αα is, the more influence the previous observations have and the smoother the series is.

3.4.5 Correlation with the Past Values

The correlation of the time series observations calculated with values of the same series at previous times is called a serial correlation, or an autocorrelation (ACF). It is used to determine the moving average (MA or q) term of the ARIMA(p,d,q) models. A partial autocorrelation (PACF) is a summary of the relationship between an observation in a time series with observations at prior time steps with the relationships of intervening observations removed. It is used to determine the autoregression (AR or p) term of the ARIMA(p,d,q) models. And it has been observed till now that the power production time series has a strong correlation with its past day value (lag of 24 hours) and also its past value 365*24 hours ago. In addition, a weekly seasonality is also observed in the energy consumption. The ACF and PACF plots for power time series data shows in Figure 3.0.23.

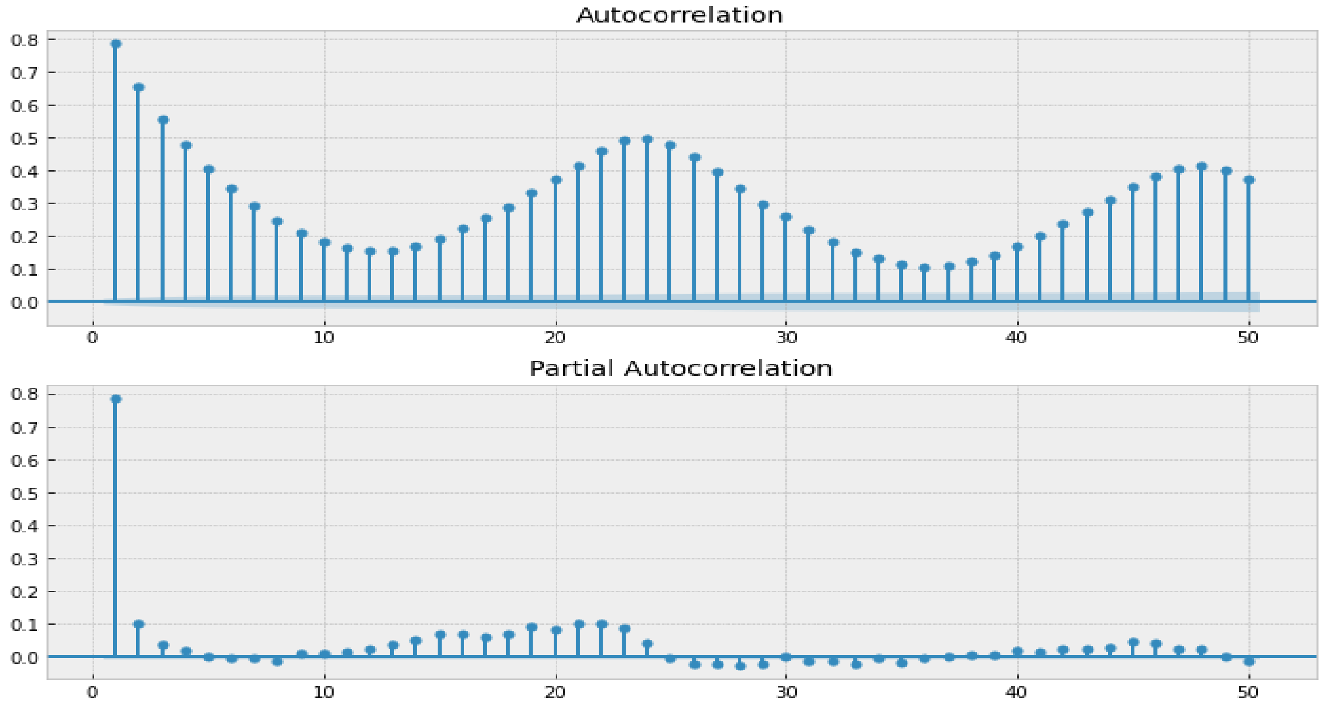


Figure 3.0.23 Correlation and autocorrelation

3.4.6 Handling Multiple Seasonality

There are two interesting time series forecasting methods called BATS and TBATS that are capable of modeling time series with multiple seasonality. The method is very generic. Under the hood, it builds and evaluates many model candidates. This results in the slowness of the computation. And SARIMAX models with Fourier series handling the multiple seasonality can perform as well as the TBATS model, so it will output for the simpler model here i.e., SARIMAX. It will need to create some extra features here to model the multiple seasonality.

3.4.7 Adding Fourier Cyclical Series for an Hour, Year, and Week Periods

XGBoost stands for extreme Gradient Boosting and is developed on the framework of gradient boosting. XGBoost is a decision tree-based algorithm that uses a gradient descent framework. It uses a combination of parallelization, tree pruning, hardware optimization, regularization, sparsity awareness, weighted quartile sketch, and cross-validation.

It is exactly what it does, boosts the performance of a regular gradient boosting model. “XGBoost used a more regularized model formalization to control over-fitting, which gives it better performance.

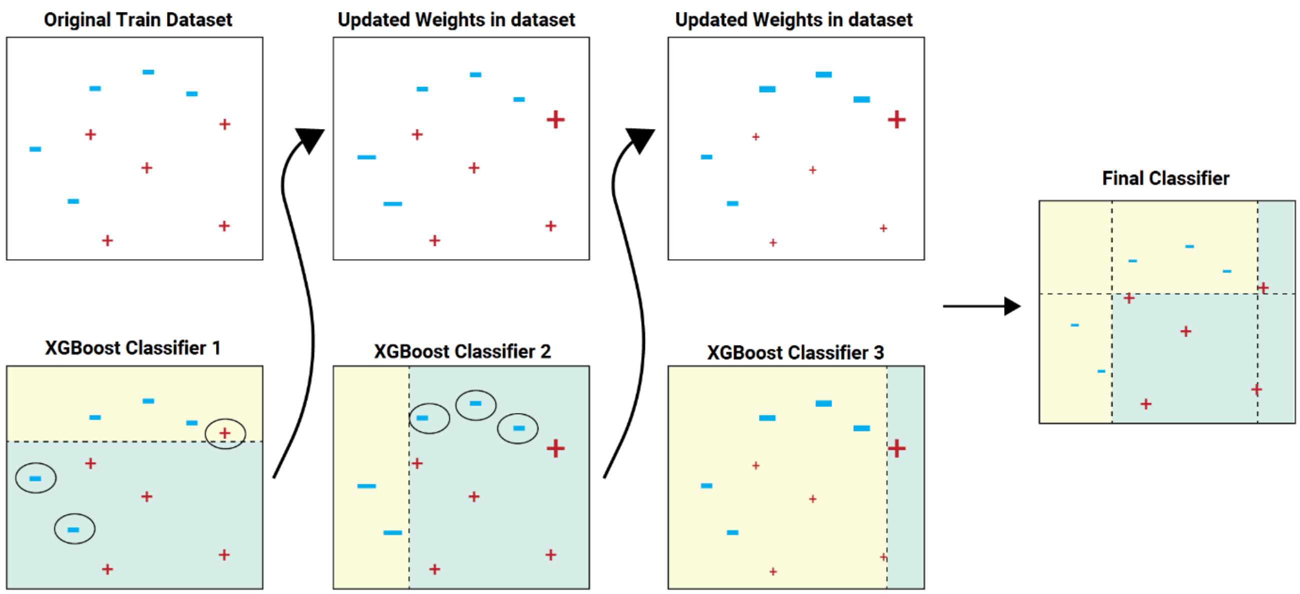


Figure 3.0.24: XGBoost schematic diagram

3.4.8 Prediction

Machine learning model onto power generation time series and use that to predict future power generation. The time series dataset has the dependent variable 'Power' which represents the power generation of the Adama II wind farm and also has independent variables wind direction and wind speed. It has used all these features to train the model and use it to predict future power values.

It can be seen that the model predicts the daily trend and seasonality pretty well but the high peaks are not captured by the model very well. It can be said the daily, weekly, and yearly seasonality was captured decently well by the model. But from the error metrics on the train and test sets, it can be observed that the model is stable and isn't overfitting.

Baseline Persistent Forecast all the models will be compared to a baseline persistent model which is simply a repetition of last year’s power production values.

3.4.9 Validation of The Model

The forecasting model validate through regression, mean absolute error, root mean squared error, and mean absolute percentage error

Regression: coefficient of determination (this can be interpreted as the percentage of variance explained by the model), $(-\infty,1](-\infty,1]$

$$R^2 = 1 - \frac{ss_{res}}{ss_{tot}} \tag{3.12}$$

Mean Absolute Error: this has the same unit of measurement as the initial series, $[0,+\infty)[0,+\infty)$

$$\text{MAE} = \frac{\sum_{i-1}^{n} |y_i - \check{y}_{i|}}{n} \tag{3.13}$$

Root Mean Squared Error: the most commonly used metric that gives a higher penalty to large errors and vice versa, this too has the same unit of measurement as the initial series $[0,+\infty)[0,+\infty)$

$$\text{RMSE} = \sqrt{(\frac{1}{2}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{3.14}$$

Mean Absolute Percentage Error: this is the same as MAE but is computed as a percentage, which is very convenient when it wanted to explain the quality of the model to management, $[0,+\infty)[0,+\infty)$

$$\text{MAPE} = \frac{100}{n}\sum_{i=0}^{n}\frac{|y_i - \hat{y}_i|}{y_i} \tag{3.15}$$

MAPE will be chosen to sort the models. MAPE helps us to understand the % error on the absolute value that can be expected from a model. The error metrics for all the models will be compared to a baseline of persistent forecast wherein simply the last year's values are used for the forecast (when forecasting over a longer window of >1 month).

CHAPTER 4: RESULT AND DISCUSSION

4.1 ADAMA II WIND FARM PERFORMANCE MODEL RESULT AND DISCUSSION

4.1.1 Validation of The Model

In this section the Adama II wind farm performance investigation developed MATLAB model is tested and validated based on the normal operation of the farm. From the starting time of the simulation, the control system is discretized for 0.1milisecond due to seated to react on discretized for analysing rush start. as bus voltage (V_{bus}) shown in Figure 4.0.1 at transient state V_{bus} is maximum and seated nicely after 0.5seconds it has got steady-state power and voltage values. As expected, the value of the output signal is approximately 153MW. Furthermore, the reactive power management system engaged after 0.5 seconds and the system becomes stable furthermore, the reactive power becomes 0MVra after 0.2 seconds of reactive power management system reaction. Active power colour yellow and reactive power colour blue as shown in Figure 4.0.1.

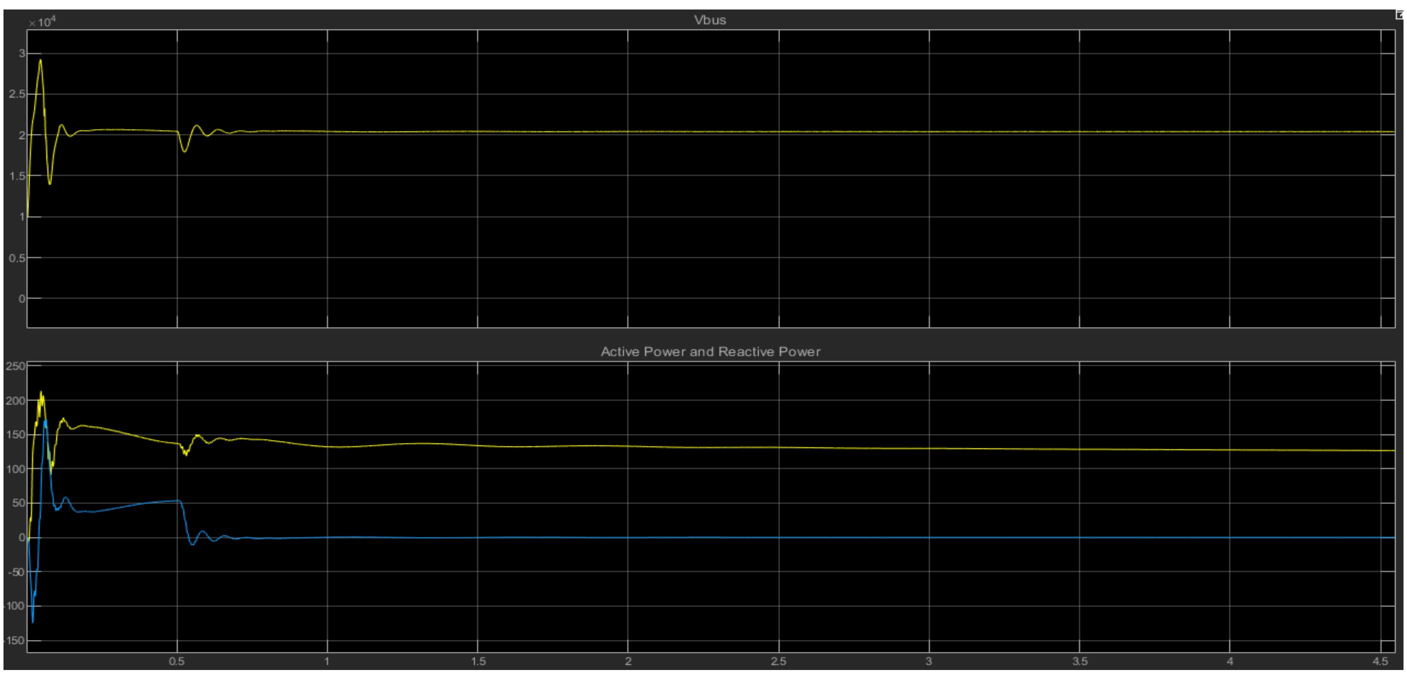


Figure 4.0.1 Adama II wind farm normal operation model simulation output

Figure 4.0.2 shows a longer duration in the wind speed profile variation will start to corresponding changes in the reactive power and also active power values as well.

Figure 4.0.2 Adama II wind farm Reactive power management system

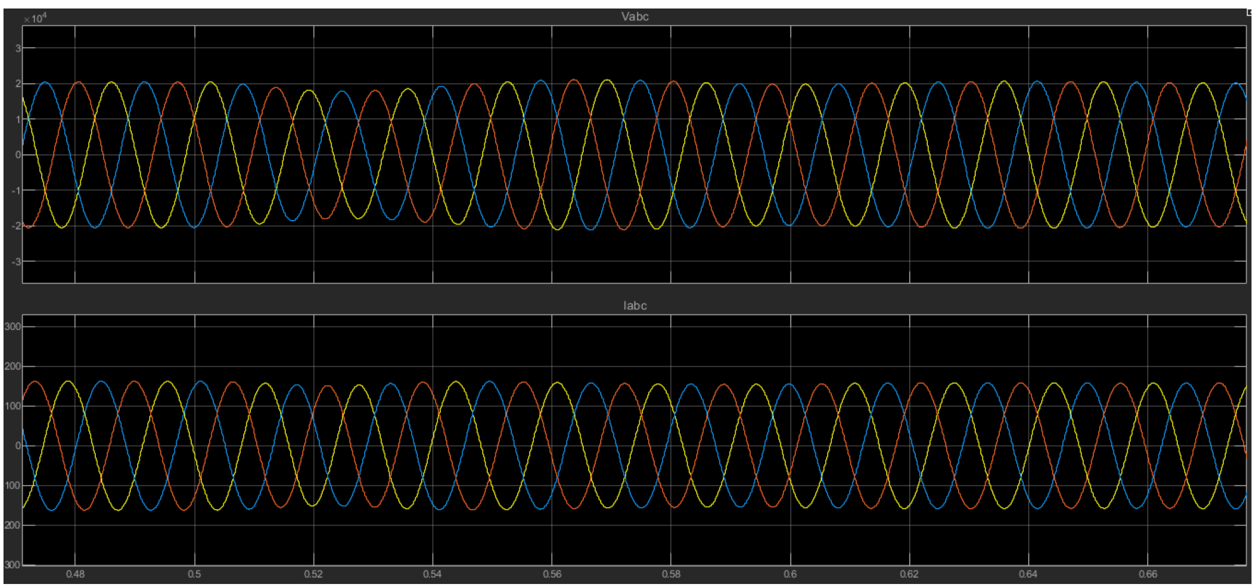


Figure 4.0.3 Adama II wind farm normal operation output signal

Figure 4.0.4**:** Turbine voltage and current

The influence of rapid change wind speed from 3.5m/s to 14.5m/s on the simulation model. Rotor shaft speed, voltage disturbance at Vbus, and the change of output power are observed after 5.3sec the system is stable through system voltage support.

Figure 4.0.5 shows when the wind speed is varying the turbine pitch angle is adjusted accordingly to overcome the wind speed effect on output power.

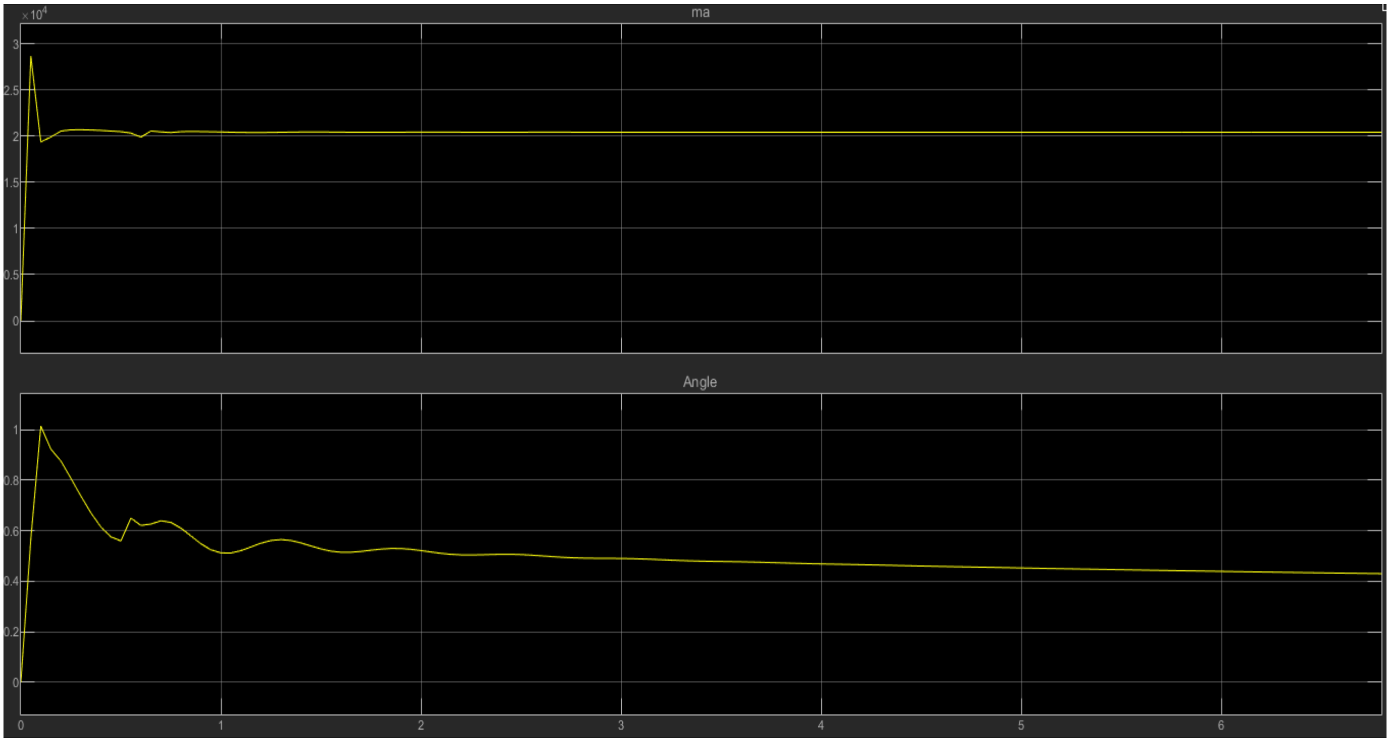


Figure 4.0.5: Turbine pitch angle adjusting based on wind speed variation

4.1.2 Short Circuit Fault Simulation Result and Discussion

Simulation for 5 seconds as Figure 4.0.6 shows the variation of various parameters concerning the simulation time. The first plot shows the voltage at the bus bar of the wind farm substation. It can be seen that when the short circuit is applied for zero seconds the voltage at this bus bar reduces to zero. And it stays at zero until the fault is cleared at 100 milliseconds and the voltage rises back to its pre-fault value.

In the second plot, the positive sequence of current contributions from the external grid and the wind farm is shown. it can be seen that during the fault the contribution from the grid is very high. The last plot shows the active and reactive power contributions from the wind farm. It can be seen that during the fault since the voltage at the point of common coupling drops to zero the real and the reactive power also drop to zero. The influence of the Adama II wind farm is a single phase-to-ground fault occurring on the bus B230, 230-KV line, and the fault is applied at 9-cycle single-phase to ground fault at t = 5 s.

As shown in Figure 4.0.6, at the voltage regulation mode of each wind turbine, the positive-sequence voltage at wind-turbine terminals (V1_B690) drops to 0.8 pu during the fault, which is above the Undervoltage protection threshold (0.75 pu for a t > 0.1 s). The wind farm, therefore, stays in service. However, if the "Var regulation" mode is used with Qref = 0, the voltage drops under 0.7 pu, and the Undervoltage protection trips the wind farm. It can now observe that the turbine speed increases. At t= 40 s the pitch angle starts to increase to limit the speed.

4.1.3.1 Specifically, Fault in Single Turbine

The top plot shows the positive sequence voltage at the wind turbine terminals it can be seen that during the fault the voltage falls but the voltage does not collapse to zero as at the point of common coupling because of the impedance between that point and the turbine.

In the bottom plots, the active current supplied by the turbine is shown in P(MW) and the reactive current in Q(MW). It can be seen that before the fault the active and reactive current is constant as soon as the fault is applied there is an initial reaction from the wind turbine and then the voltage support mode for fault ride through begins to exert the influence. The reactive current delivered is determined by the voltage dip and the k factor and increased. The active current is reduced since priority is given to the reactive current injection post fault the values return to their pre-fault values. Finally, the impact of a single phase-to-ground fault occurring on the 690V line at cluster 1 bus turbine S15. Apply the fault at 9-cycle single-phase to ground fault at t = 5 s. a positive-sequence voltage at wind-turbine terminals (V1_B690) drops to 0.8 pu during the fault, which is above the Undervoltage protection threshold (0.75 pu for a t > 0.1 s). The wind farm, therefore, stays in service. However, if the "Var regulation" mode is used with Qref = 0, the voltage drops under 0.7 pu, and the Undervoltage protection trips the wind farm.

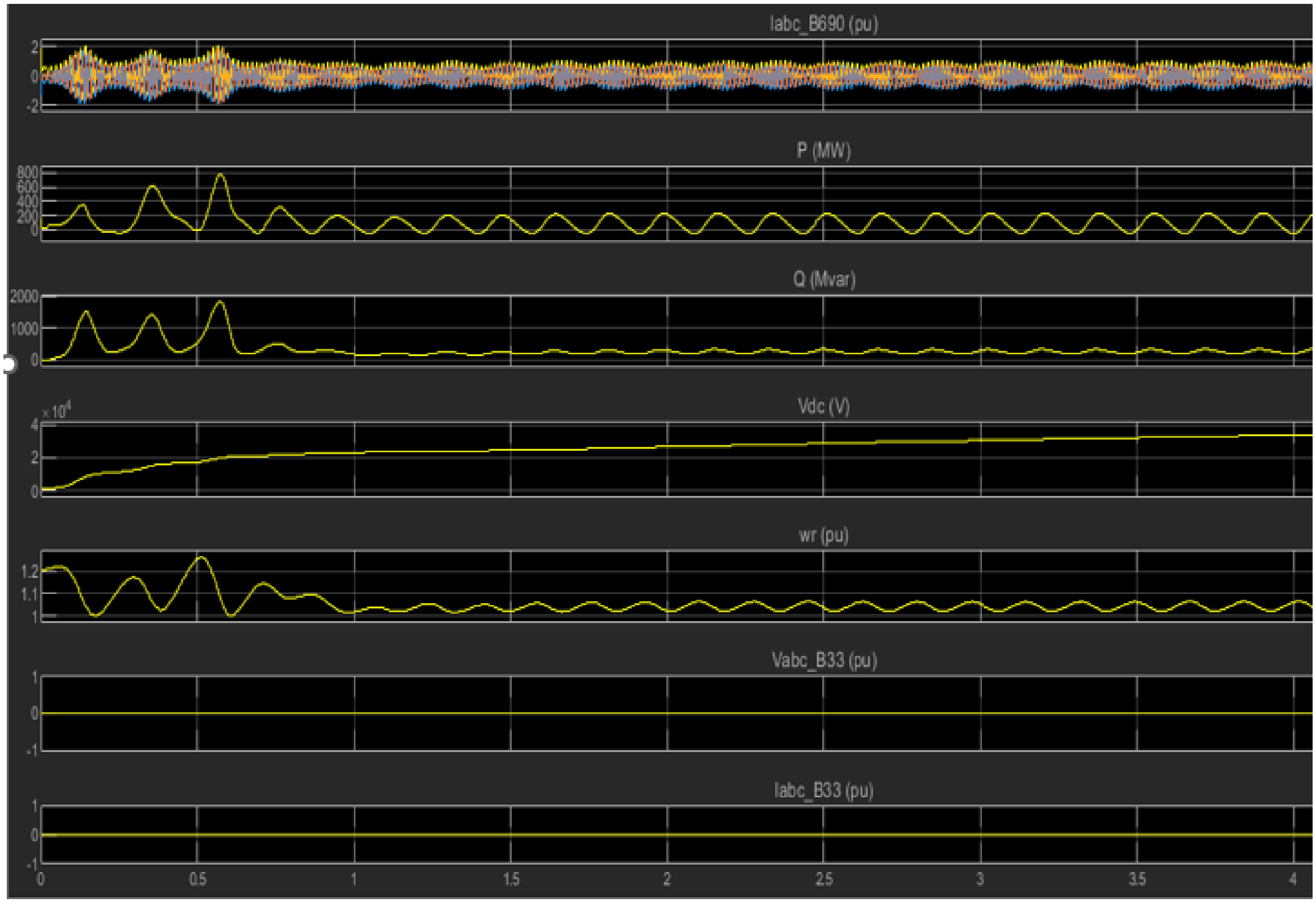


Figure 4.0.6: wind farm fault at a common coupling point

At the steady-state operation of the Wind farm and its dynamic response to voltage sag resulting from a remote fault on the 230-kV system substation common coupling point and block modeling the voltage source and a six-cycle 0.5 pu voltage drop are seated at t=0.03 s

When the simulation starts initially the DFIG wind farm produces 153 MW. The corresponding turbine speed is 1.2 pu of generator synchronous speed. The DC voltage is regulated at 1150 V and reactive power is kept at 0 Mvar. At t=0.03 s the positive-sequence voltage suddenly drops to 0.5 p.u. causing an oscillation in the DC bus voltage and the DFIG output power. During the voltage sag, the control system tries to regulate DC voltage and reactive power at their set points (1150 V, 0 Mvar). Finally, the system recovered after 4 cycles as shown in the P(MW) plot.

4.1.4 Control Faults Simulation Result and Discussion

Wind farm reactive power control is based on the secondary voltage control concept. At the primary level, the wind turbine controller monitors and controls its own positive sequence terminal voltage with a proportional voltage regulator and control producing more reactive power. At the secondary level, the Adama II wind farm controller monitors the reactive power at POI and controls it by modifying wind turbine controller reference voltage values via a PI reactive power regulator Usually, the wind farm transformer has an OLTC to keep MV collector bus voltage around its nominal value. Active power at POI depends on the wind speed variation at each wind turbine inside the farm.

Figure 4.0.7 shows the voltage and current on each side of the converter output per unit and filtered the input measuring filters are a low pass type the compute variable blocks complete the variables used by the control and protection system. At PLL determine the voltage angle and frequency and help to achieve the transformation from the ABC domain to the DQ0 domain which is used for control purpose

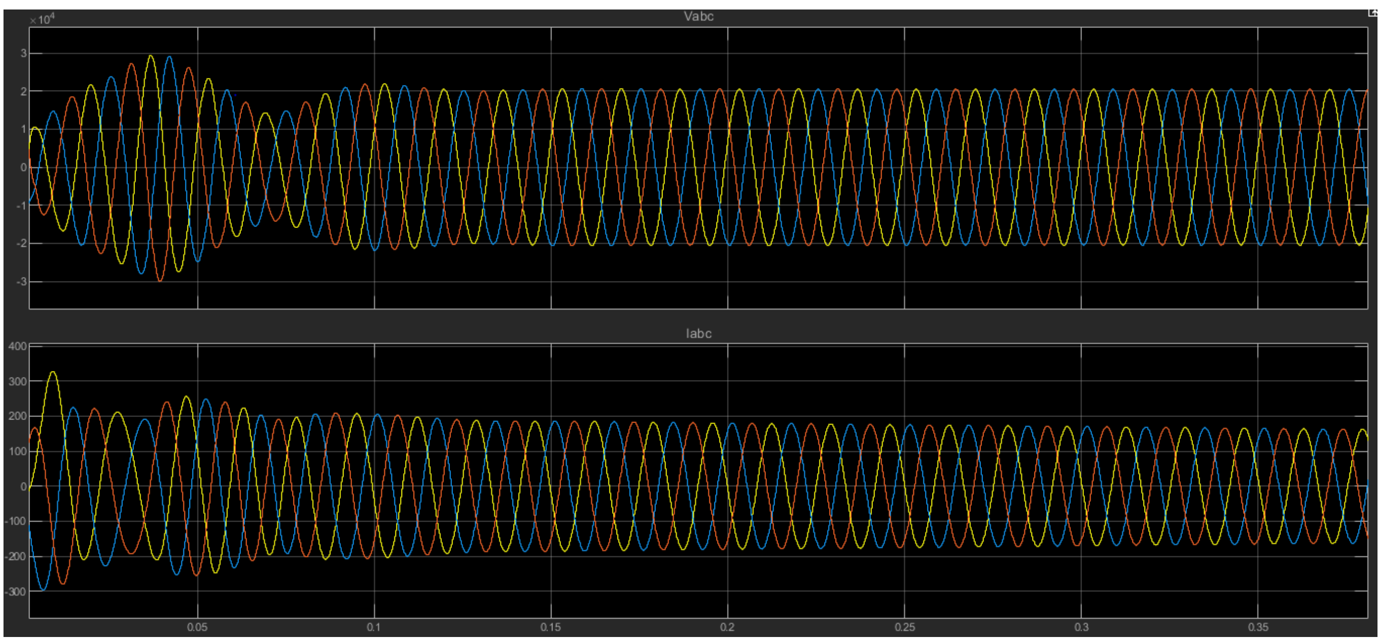


Figure 4.0.7: Control faults simulation output.

The pitch control block limits the mechanical power extracted from the wind speed by increasing the pitch angle when the wind speed is above its rated. The protection system block contains cut-in and cut-off wind speed relays. Low voltage and over-voltage relays mash inside converter and grid side converter over current protections and DC resistive chopper control the LVRT and OVER key functions. DQ0 domain control is the most commonly used controller by wind turbine manufactures in the industry some of its main advantages are that it allows decoupling control of real and reactive powers. The control power is controlled by the Q axis of the rotor side converter and the reactive power is only controlled by the D axis of the same controller.

Another advantage of this control type is that when the system is balanced the D and Q axis current and voltage are constant in a steady-state they are therefore easier to control than synodal quantity on the machine side the DQ transformation angle follows the induction machine flux the Q component corresponds to the real power and the D component to the reactive power therefore by controlling the Q axis current the converter controls the machine electrical power the two-level control is used and built with an outer loop and an inner loop the reference of the outer loop is the active power and it produces the reference of the inner loop the Q axis current reference the outer loop reference is provided by the maximum point tracking or MPPT and is set to get the maximum power out of the wind this depends on the rotation speed and some optimization curves to find the optimal power available.

The positive sequence terminal voltage reference is modified by the wind farm controller to achieve the desired reactive power output of the wind farm.

$$Idr = Kv(v' - V + wt) + idr - m \tag{4.1}$$

The output of the loop is the D axis current reference which will be the reference for the inner loop which is the fastest one that produces the D axis voltage reference to follow the current reference before being used by the inner loop the current reference is limited by the idq limiter block so the converter does not exceed its current capabilities which could cause hardware damage. the gains of the outer loop PI controller for the d-axis are calculated based on the DC bus capacitance.

As shown in Figure 4.0.7 and Figure 4.0.8 voltage and current and the wind farm produce below 1.87 MW. At t = 5 s, the voltage falls below 0.9 pu, and at t = 5.22 s, the protection system trips the plant because an Undervoltage lasting more than 0.2 s has been detected (look at the protection settings and status in the "Plant" subsystem). The plant current falls to zero and motor speed decreases gradually, while the wind farm continues generating at a power level of 1.87 MW. After the plant has tripped, 1.25 MW of power (P_B33 measured at bus B33) is exported to the grid.

Now, change the wind turbine control mode to "Voltage regulation" and repeat the test. You will notice that the plant does not trip anymore. This is because the voltage support provided by the 5 Mvar reactive power generated by the wind-turbines during the voltage sag keeps the plant voltage above the 0.9 pu protection threshold. The plant voltage during the voltage sag is now 0.93 pu.

As Figure 4.0.8 shows when the fault occurs the system stopped responding and the output power will become zero immediately.

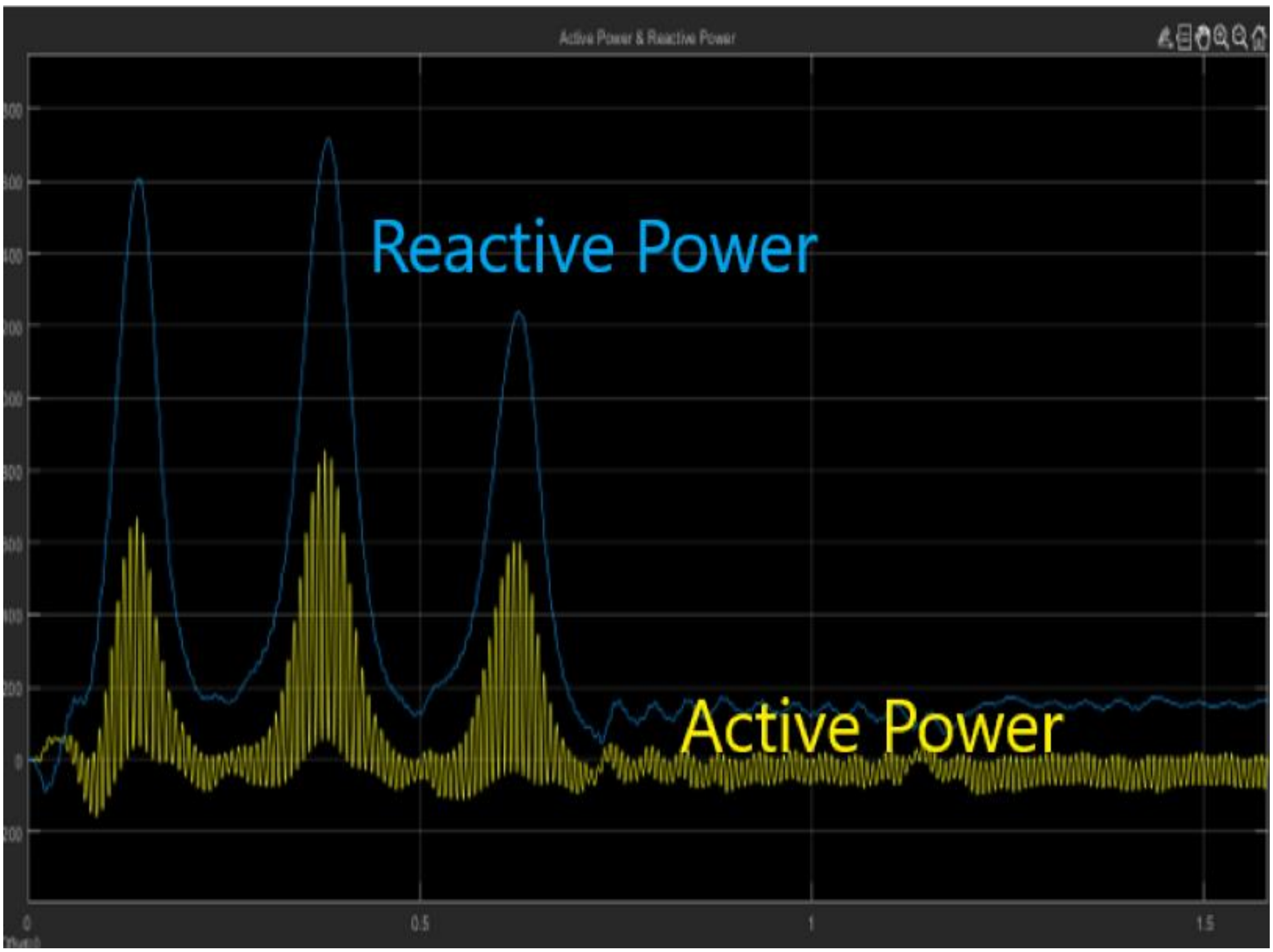


Figure 4.0.8: Active Reactive power control system fault output

4.1.5 Rapid wind Speed Variation Impact Simulation Result

Wind speed varies due to the influence of meteorological fluctuations over seconds, minutes, hours, days, months, seasons, and years. Hence in weak grid DFIG type wind farms can be obliged to operate under unbalanced grid voltage where nonlinear loads produce unbalances of grid voltage.

Initially, wind speed is set at 8 m/s, then at t = 5s, wind speed increases suddenly at 14 m/s. Start simulation and observe the signals on the "Wind Turbine" scope monitoring the wind turbine voltage, current, generated active and reactive powers, DC bus voltage, and turbine speed. At t = 5 s, the generated active power starts increasing smoothly (together with the turbine speed) to reach its rated value of 153 MW in approximately 15 s. Over that time frame, the turbine speed will have increased from 0.8 pu to 1.21 pu. Initially, the pitch angle of the turbine blades is zero degree and the turbine operating point follows the red curve of the turbine power characteristics up to point D. Then the pitch angle is increased from 0 deg to 0.76 deg to limit the mechanical power. Observe also the voltage and the generated reactive power. The reactive power is controlled to maintain a 1 pu voltage. At nominal power, the wind turbine absorbs 0.68 Mvar (generated Q = -0.68 Mvar) to control voltage at 1pu. When changing the mode of operation to "Var regulation" with the "Generated reactive power Qref " set to zero, we observe that voltage increases to 1.021 pu when the wind turbine generates its nominal power at unity power factor.

Local variations are largely equal to geographical diversity, and will generally remain inside ±5 percent of installed wind power capacity at the regional level. The most significant variations arise from the passage of storm fronts when wind turbines reach their storm limit (cut-out wind speed) and shut down rapidly from full to zero power. However, due to the averaging effect across a wind farm, the overall power output takes several minutes to reduce to zero. During the summery season, the wind speed varies from the rated speed of 14.5m/s to 0m/s analogous to wind speed the power generation goes from 153MW to 0MW.

As shown below Figure 4.0.8 and Figure 4.0.9 depicted in millisecond wind speed variations will be an issue for power system stability used for balancing when wind power penetration reaches the point at which variations in supply the voltage support try to meet the demand and stabilize the system.

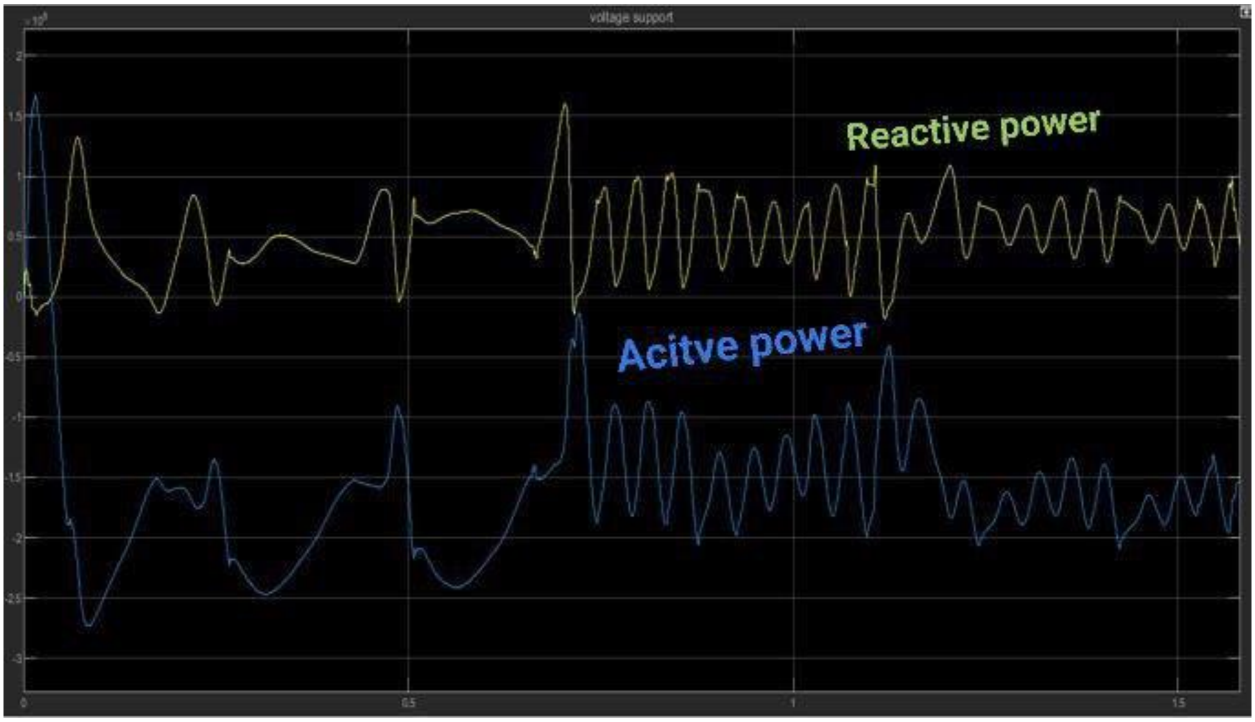


Figure 4.0.9: Voltage support reacting when the speed varies in millis

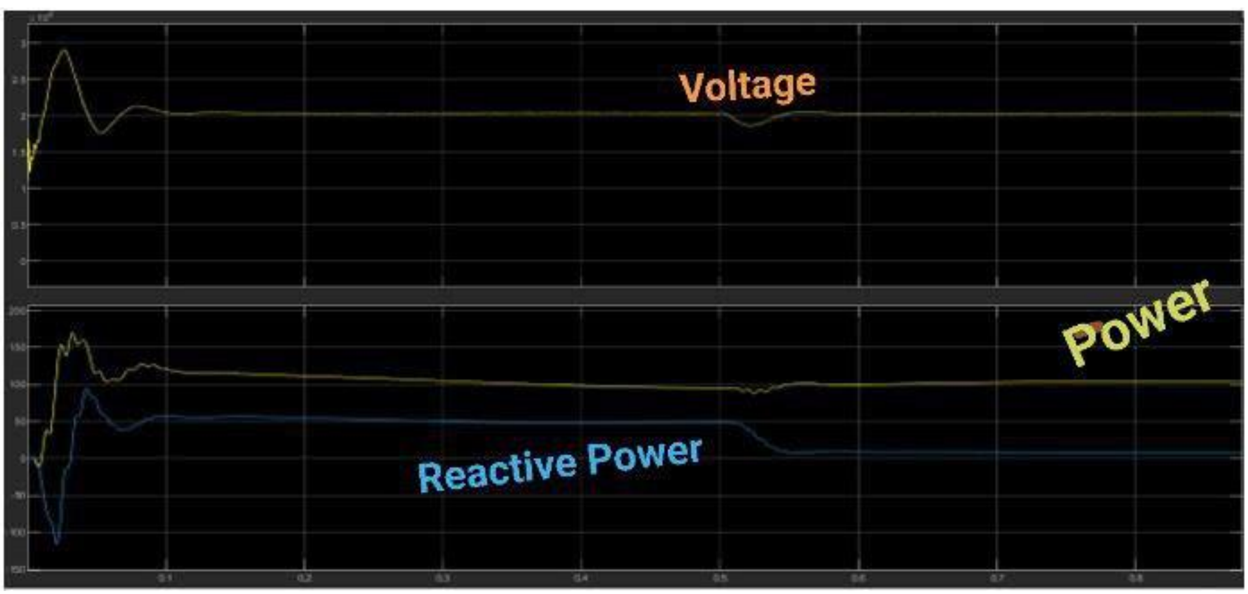


Figure 4.0.10: Making the stable output of wind farm

The power generation performance of the Adama II wind farm was analyzed using power and energy production performance indices. From a production analysis aspect, the wind farm delivers average power of 150 MW to the grid with a maximum of 151.09 MW and a minimum of 0 MW.

The annual average wind speed of the Adama II Wind power project site at 70m height ranges from 8.48$^{m}/_{s}$ to 9.01$^{m}/_{s}$, and the annual wind power density ranges from 449.54$\frac{W}{m^2}$ to 496.00 $\frac{W}{m^2}$. The annual average wind speed at 50m height ranges from 8.11$^{m}/_{s}$ to 8.68$^{m}/_{s}$, and the annual wind power density ranges from 352.88 $\frac{W}{m^2}$ to 441.35$\frac{W}{m^2}$. According to International Standards, the Adama II Wind power project can be classified as a level 6 wind power plant, which means the Adama II Wind power project with a great wind resource potential. The annual average electricity generation of the Adama II Wind power project is 461.404GWh, the equivalent full load hour is 3016h, and the capacity factor is 0.34[30]. The energy delivered over the year 2021/22 G.C has been 425.28 GWH. These demonstrate that based on the current status, the wind farm performance is good and within the design range. The second aspect is an analysis of harmonic emission from the wind farm as the result of frequency converters and other nonlinear loads. The harmonic current data are collected at one of the points of common coupling (PCC) which is at 33 KV bus bar systems, where 3rd and 5th current injection harmonic filters are installed. Using MATLAB software, the steady-state harmonic load flow analysis of the wind farm at a 33KV bus-bar system is performed. It has been found that the results of mathematically analyzed Total Harmonic Distortion (THD) current and voltage values are almost similar to that of simulated THD output of current and voltage. The wind farm harmonic current emission with the maximum calculated value of 5.96 % is found to be within the permissible limit set by the international standard at the selected PCC which is 7%.

CHAPTER 5 LONG-TERM POWER PRODUCTION FORECASTING FOR ADAMA II WIND FARM RESULT and DISCUSSION

5.1 Validation of The Models

To validate this time series model, apply through training the model on a small segment of the time series from the beginning until some *t*, make predictions for the next *t+n* steps, and calculate an error. Then, expand the training sample to *t+n* value, make predictions from *t+n* until *t+2*n*, and continue moving our test segment of the time series until we hit the last available observation. As a result, we have as many folds as *n* will fit between the initial training sample and the last observation. This can be established using Sklearn. model selection's time series split module. The model prediction steps are shown in below Figure 5.0.1.

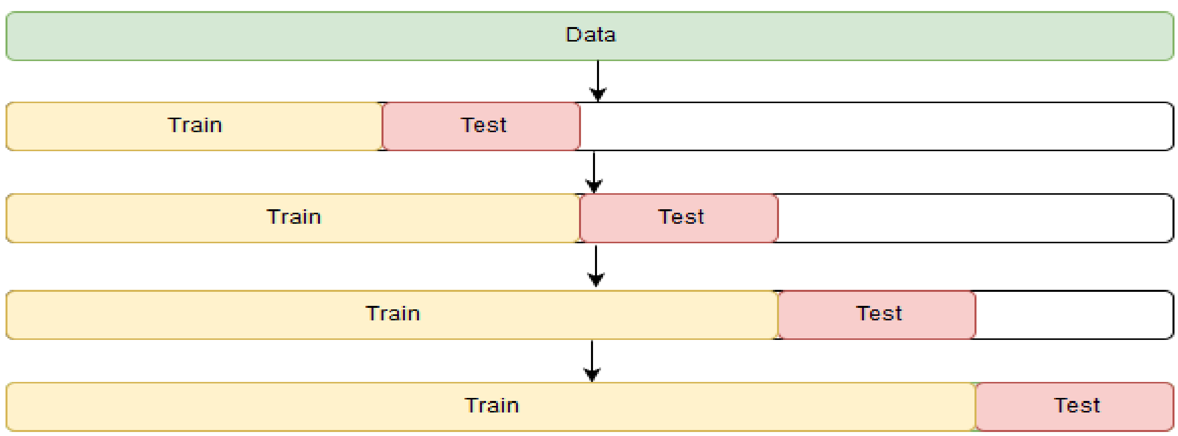


Figure 5.0.1: Prediction process

The model performance will be evaluated using multiple error parameters: Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) Root Mean Square (RMS) error, etc. [107]

- **Baseline Persistent Forecast**

All the models will be compared to a baseline persistent model which is simply a repetition of last year's Power generation values.

Error metrics for model Baseline Persistent forecast, repeat last year

Table 5.0.1 Persistent forecast

RMSE or Root mean squared error:	**Variance score**	**Mean Absolute Error**	**Mean Absolute Per centage Error**
482.69	-0.02	314.20	15 %

The Power production for winter months is wider spread and is more right-skewed towards higher values as compared to summer months. for reasons discussed previously. Also, the trend of maximum power generation shifting towards lower values is more dominant for winter months as compared to the summer months as shown below in Figure 5.0.2

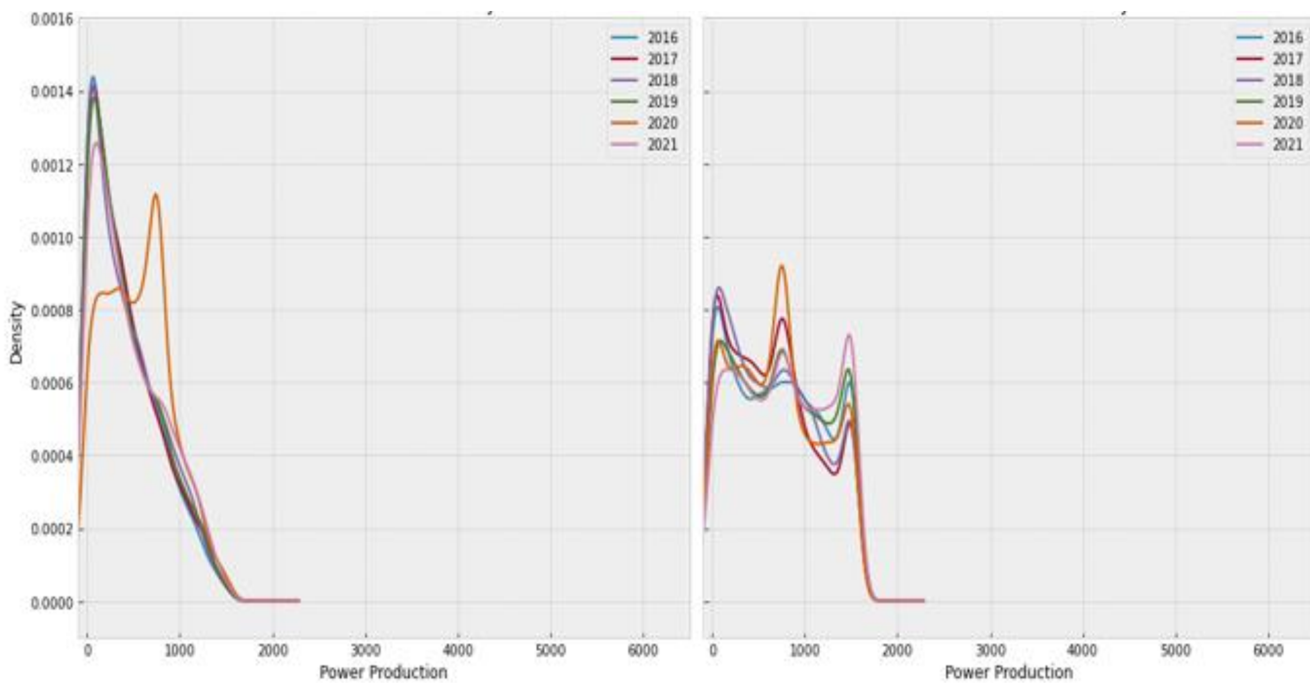


Figure 5.0.2: Farm power generation in a seasonal curve

5.2 Elastic Net Regression

It has conducted to fit the elastic net and RF models to the above dataset with Fourier series
Elastic net regression on data with Fourier terms

- Trying Elastic net regression on the above-reduced X space
- Tuned ElasticNet l1 ratio: {'alpha': 1.0, 'l1_ratio': 1.0}

- Tuned ElasticNet R squared: 0.8753023429651108
- Tuned ElasticNet RMSE: 48.6965562197244

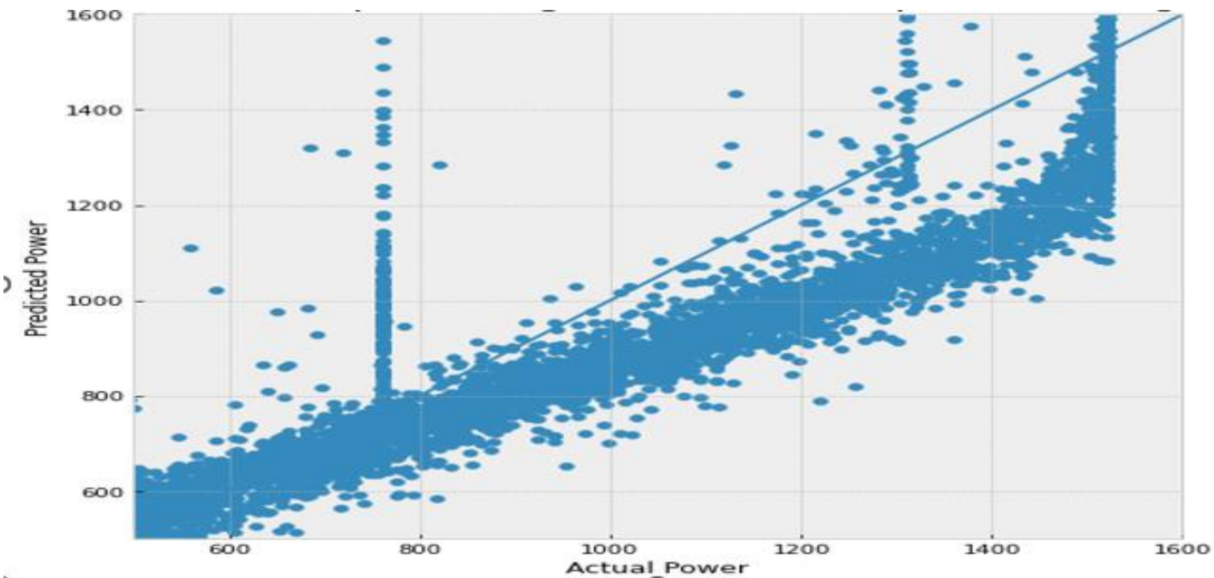


Figure 5.0.3: Actual v predicted power using Elastic net optimal linear regression

5.3Random Forest Regression

Applying SkLearn module for training random forest regression model, specifically the RandomForestRegressor function. The Random Forest doesn't perform very well on a time series problem and most often than not it will overfit the data and predict poorly on the test set. But the performance of random forest on a time series problem can be improved by some feature engineering.

Fitting 5 folds for each of 10 candidates, totaling 50 fits

{'n_estimators': 73, 'max_features': 'auto', 'max_depth': 5}
Tuned Random Forest errors on the training set

Error metrics for model Tuned Random Forest with reduced hour space

Table 5.0.2: Error metrics for model Tuned Random Forest with reduced hour space

RMSE or Root mean squared error:	Variance score	Mean Absolute Error	Mean Absolute Percentage Error
109.70	0.95	51.77	inf %

- **Tuned Random Forest errors on the test set**

Error metrics for model Tuned Random Forest with reduced hour space

Table 5.0.3: Error metrics for model Tuned Random Forest with reduced hour space

RMSE or Root mean squared error:	**Variance score**	**Mean Absolute Error**	**Mean Absolute Pe rcentage Error**
113.58	0.94	68.40	55%

As shown in the above result random forests do have poor accuracy.

5.4 SARIMAX Model

The SARIMAX model takes many inputs which require some tuning to be able to pick the best model parameters. $pmdarima$ package's auto Arima module automates this task and gives the best model by taking in some input ranges.

As shown below in Figure 5.0.4 the first-week forecast is well but even at the end of the first week the forecasting performance decreases and the confidence interval values grow larger beyond the scale of the range of the power generation values. Thus, the SARIMAX model was not able to capture long-term trends but it did well on 1 week ahead forecast. SARIMA models don't capture multiple seasonality well and are also very time-consuming. So, it won't be the first choice if it needs both a quick and accurate forecast. Errors for 1 hour ahead forecasts weren't calculated above for the SARIMAX model (by using dynamic=True).

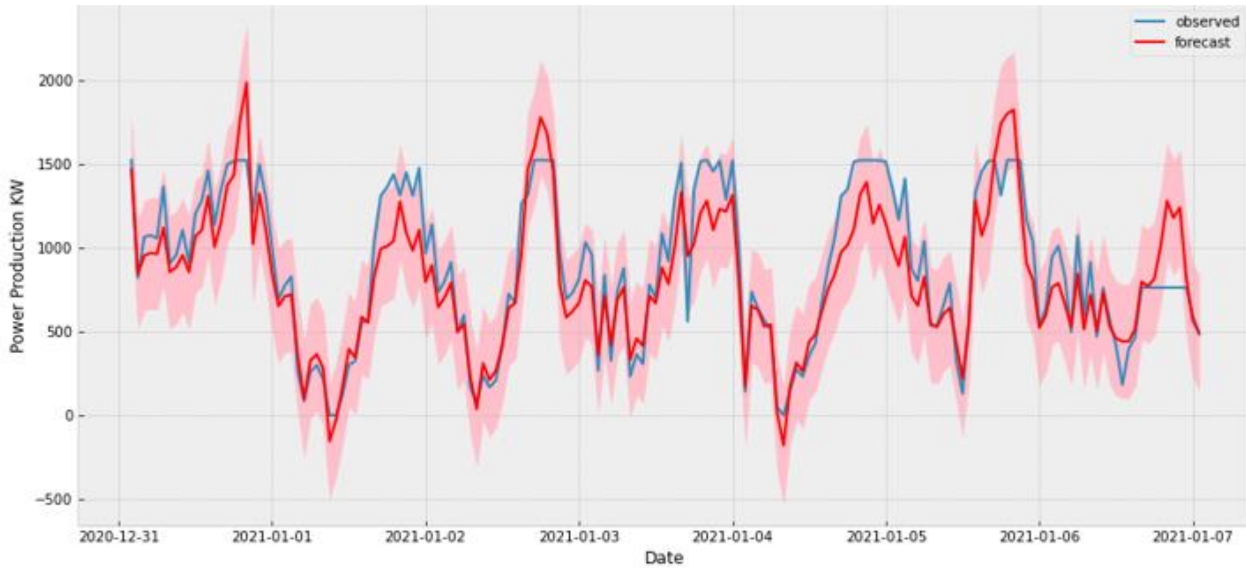


Figure 5.0.4: Testing the SARIMAX for the 1st week (2021/01/01-07)

It has shown that the first-week forecast is pretty well but even at the end of the first week the forecasting performance decreases and the confidence interval values grow larger beyond the scale of the range of the energy consumption values. Thus, the SARIMAX model was not able to capture long-term trends, but it did well on 1 week ahead forecast.

Table 5.0.4. Error metrics for model SARIMAX (2,1,1) x (1,0,1,24) with Fourier terms 1 week (2021/01/01-2021/01/071)

RMSE or Root mea n squared error	**Variance score: 0.81**	**Mean Absolute Erro r**	**Mean Absolute Perc entage Error**
199.39	0.81	80.22	15.3

As the above result observed for quick and accurate forecasting has not preferred SARIMA model because of its characteristics like unable to treat well multiple seasonality and it’s time very time-consuming. Errors for 1 hour ahead forecasts weren't calculated above for the SARIMAX model (by using dynamic=True) because the result is low accurate as compared to the persistence model.

5.5 XGBoost Model

XGBoost (Extreme Gradient Boosting) belongs to a family of boosting algorithms and uses the gradient boosting (GBM) framework at its core. It is an optimized distributed gradient boosting library. XGBoost is well known to provide better solutions than other machine learning algorithms. It is not often used for time series, especially if the base used is trees because it is difficult to catch the trend with trees, but since our data doesn't have a very significant trend and also since it has multiple seasonality and depends significantly on an exogenous variable like temperature, it has to try XGboost to see how it performs on the time series data of power production. The extreme gradient boosting simplified equation is

$$Fm(x) = Fm - 1(x) - \alpha Gm(x) \quad 5.1$$

The current value m (think about it as the present) uses the past information(m-1) and gets adjusted by new present evidence (G) with a certain weight.

5.5.1 Feature Importance

Feature importance is analyzing the most influential feature from below Figure 5.0.5, observed that the day of the year was most commonly used, followed by an hour and year. A month has the least importance.

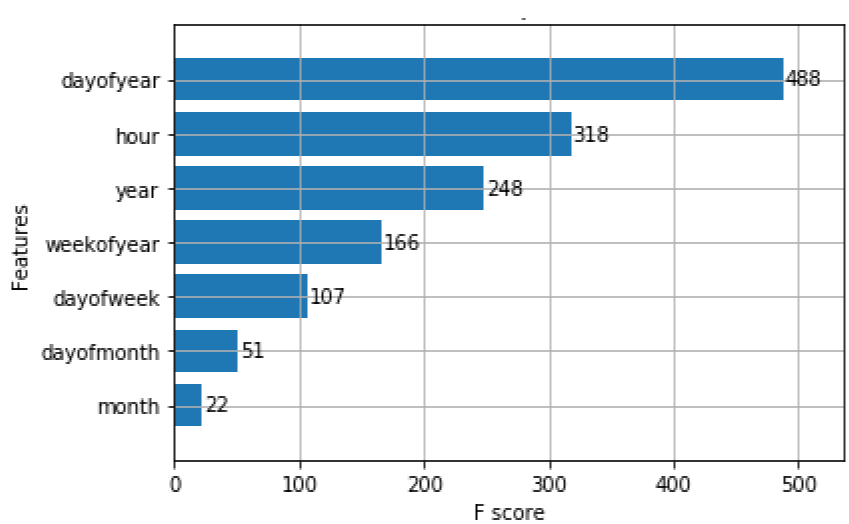


Figure 5.0.5: Feature importance

Table 5.0.5. Error metrics for model XGBoost with Fourier terms; monthly MAX

RMSE or Root mea n squared error	**Variance score: 0.81**	**Mean Absolute Erro r**	**Mean Absolute Perc entage Error**
139.11	0.79	102.57	6.83%

As the validation mean absolute percentage error result 6.83% XGBoost perform well for long time forecasting.

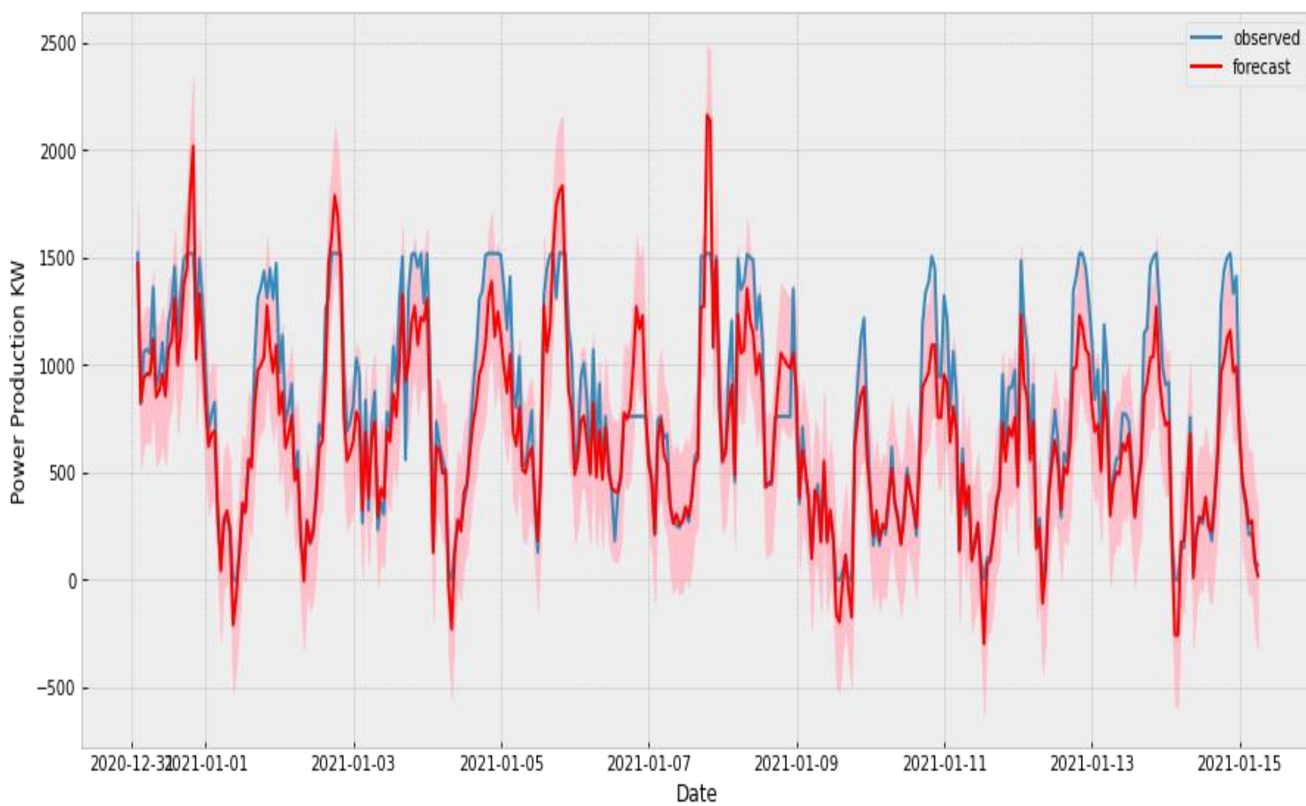


Figure 5.0.6: XGBoost one month a head forecasting result

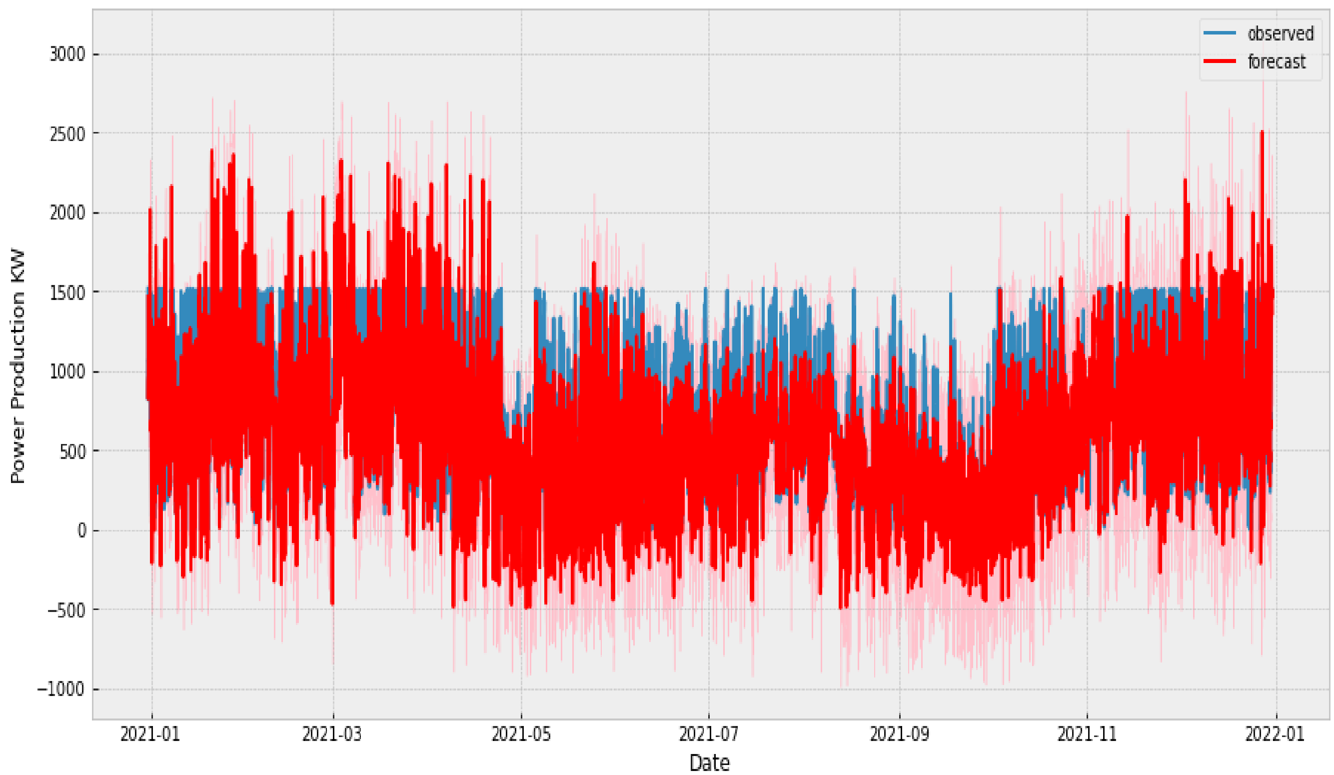


Figure 5.0.7: XGBoost a year head forecasting result

As show the output of XGBoost a year ahead prediction in Figure 5.0.7 and Table 5.0.6 XGBoost model has the Mean absolute percent accuracy (MAPA) of 92.7%. hence the model provides accurate result relative to the other applied models and Adama II wind farm could apply this model to get accurate forecasting result.

Table 5.0.6. Error metrics for model XGBoost with Fourier terms; yearly MAX

RMSE or Root mean squared error	**Variance score**	**Mean Absolute Error**	**Mean Absolute Per centage Error**
128.86	0.83	76.81	7.33%

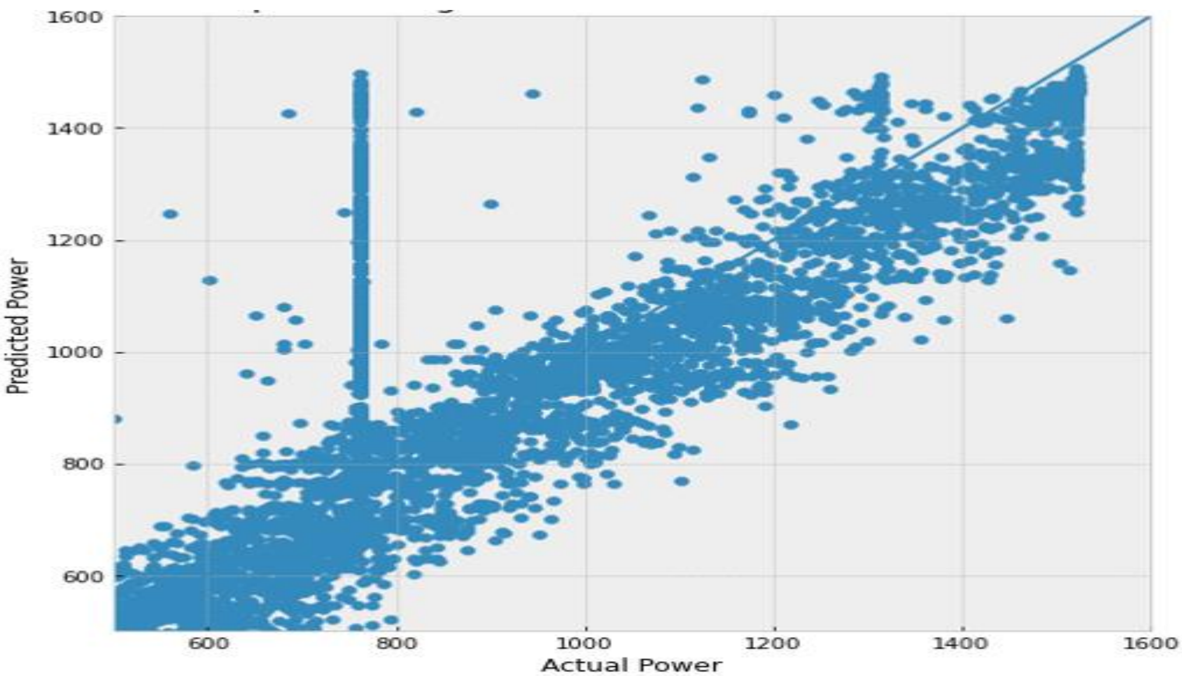


Figure 5.0.8: Actual vs Predicted power using tuned XGBoost with Fourier terms

5.6Power Curve

Power forecasting power curve sample turbine N02, N15 and S02 shown below Figure 5.0.9

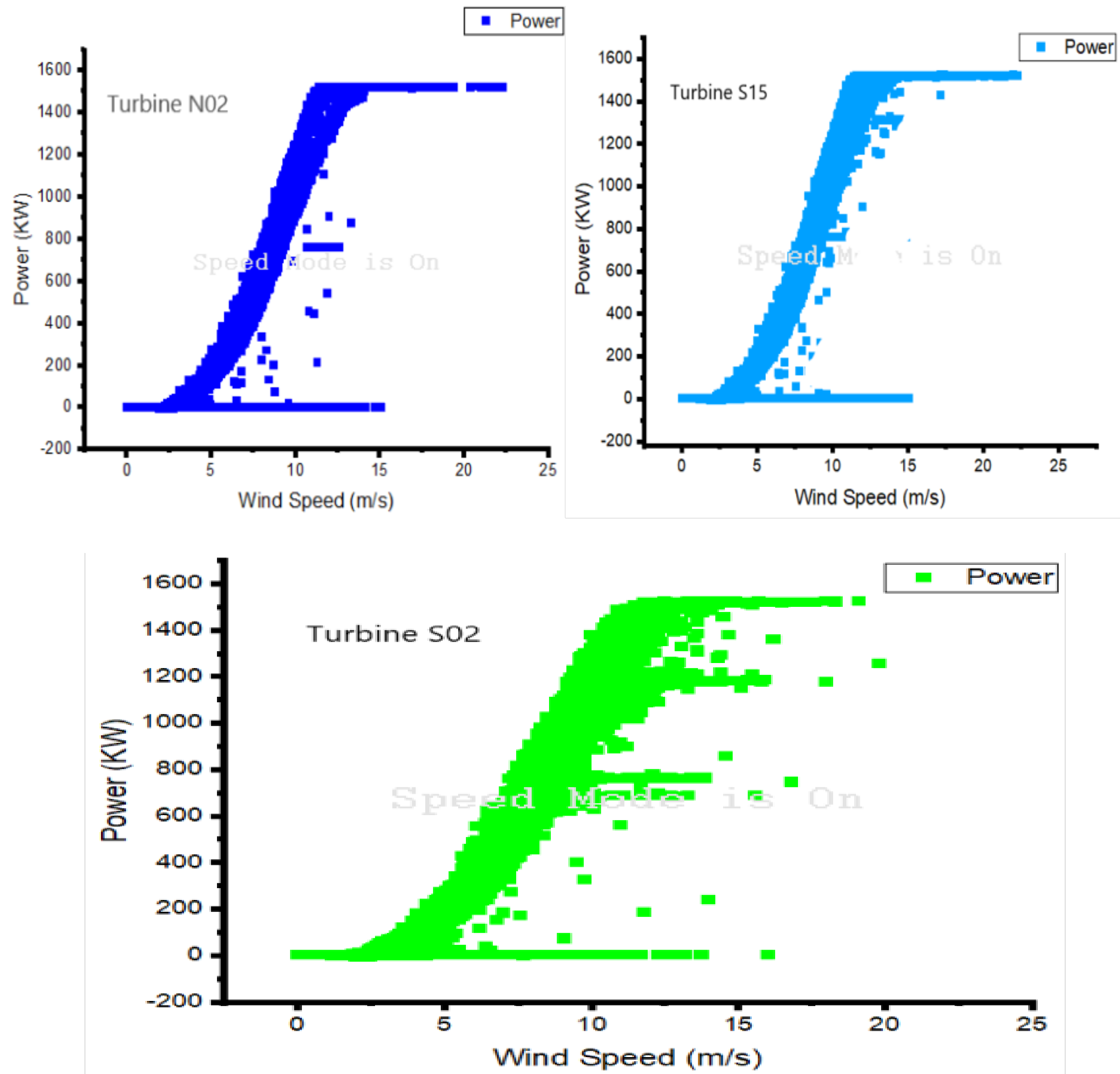


Figure 5.0.9: Operational turbine power curve

Due to the sensitivity of wind nature results from the predicted power data due to the production trend, and power difference due to 'wind farm roughness'. The production trend relative to energy production falls in line with the estimated production trend. The production difference percentage is calculated between estimated energy production and actual power generation. The difference percentage is then compared with 'distance between wind farm and measuring station', 'wind farm roughness’, and ’roughness difference percentage’ (i.e., difference in roughness between wind farm terrain and measuring station terrain). As shown in Figure 5.0.9 turbine S02's forecasted power curve is scattered due to the front turbine S01 creating turbulence on the back turbine of S02 received. not only the wind speed is lower but also the wind speed behind the rotor is lower and small there is a wake and turbulence of 20% to 30% wind speed lower relative to the front turbine due to the former air wake.

CHAPTER 6 CONCLUSION & RECOMMENDATION

6.2 Conclusions

Adama II wind farm performance analysis and investigate MATLAB modeled through analyzing the impact of control and short circuit fault. Furthermore, speed variation impact on its performance. The performance analysis demonstrates that Adama II wind farm performance is good and within the design range. Basically, Adama II wind farm delivery 0MW upto 153MW power to gird, during maintenance and some grid and turbine faults it might be failed to delivery as its capacity. Main reason to downtime are due to grid fault, night time due to light load at night Adama II wind farm don’t have voltage regulator to cop up its power fluctuation. Based on the performance the thesis develops different models to forecast the Adama II wind power. The generation power of each wind turbine is highly dependent on wind speed and has strong multiple seasonality - daily, weekly, and yearly. But there can be other factors causing the outdoor temperature and wind direction. The best way to capture the trend, which is a combination of all the above factors and maybe more, is to make the model learn the trend over a long period (more than six years at least). The seasonality is an important part of predicting the power production so getting that part right was also very crucial for improving the model's performance.

Different models were tried and presented a summary of the error metric for each model including the baseline model where today's power production is similar to the last year's power production at the same hour: A model with "all lags" and "1 week" at the end of their names are limited to 1-hour ahead and 1-week ahead forecasts, respectively. All other models have a forecast window of roughly 1 year ahead. And the model with "daily max" at the end compares the forecasted daily max with the actual daily max. The rest of the models compare hour-to-hour energy prediction. The long-term forecast accuracy will also depend on the forecast accuracy of independent variables like wind speed and outdoor temperature. In this model applied a test set of 2021 year actual data dependent and independent variables of dataset. Based on the MAPE and RMSE scores, the XGBoost model with the Fourier terms has performed very well, predicting a forecasting window of 12 months ahead. For hourly data with multiple seasonality that is a good impressive result.

For long-term forecasts most of the models have performed better than the baseline persistence model and the best model (XGBoost) gives a MAPE of 6.83% compared to the baseline error of

9.23% on the test set. The RMSE, R2, and MAE values are also considerably lower than the baseline model. While comparing the model SARIMA does comparably well for short-term hour-ahead or week-ahead forecasts. So, moderate result any of the models given above using lag variables should be good for short-term forecasts (92-95% R2 and 1-3% MAPE). The elastic net should be used for short-term forecasts, given it had the highest accuracy and also the model training time is very less compared to SARIMAX. SARIMA performs badly on long-term forecasts and doesn't capture the multiple seasonality well. Maybe more feature engineering can be done to help SARIMA identify multiple seasonality but given how time-consuming the model training for SARIMA is, it is better to focus the resources on other models.

6.3 Recommendations

The performance analyses demonstrate that based on the current status, the wind farm performance is good and within the design range. ` Adama II wind farm delivery 0MW up to 153MW power to gird, during maintenance and some grid and turbine faults it might be failed to deliver as its capacity. The main reason for downtime is due to grid fault, night time due to light load at night Adama II wind farm don't have voltage regulator to cop-up its power fluctuation. To deliver Adama wind farm required to apply

i. Load side management to respond to power imbalance loads need to be controlled accordingly by reducing or increasing power demand[108].

ii. Appling energy storage can reduce the variability of output power by providing a higher energy output for a given capacity at the delivery point and it ensures the availability of firm power for a particular and required period[109].

iii. Adama II wind farm need to install voltage regulator like hydropower plants to control the output voltage by stabilizing the fluctuation that enables the plant to deliver 24/7

iv. Forecasting future energy production range minutes, hours, days, months, and years ahead prediction enables the farm to control surplus energy production

6.4Future Work

Future work as further expansion shall be on downtime detail analyze the failure rate and downtime of wind turbines and wind farms and detail investigation of other wind farm power quality parameters such as frequency response and active reactive power control. Furthermore, Try more methods where wind farm time series models and other traditional machine learning models could be combined for better-improved accuracy.

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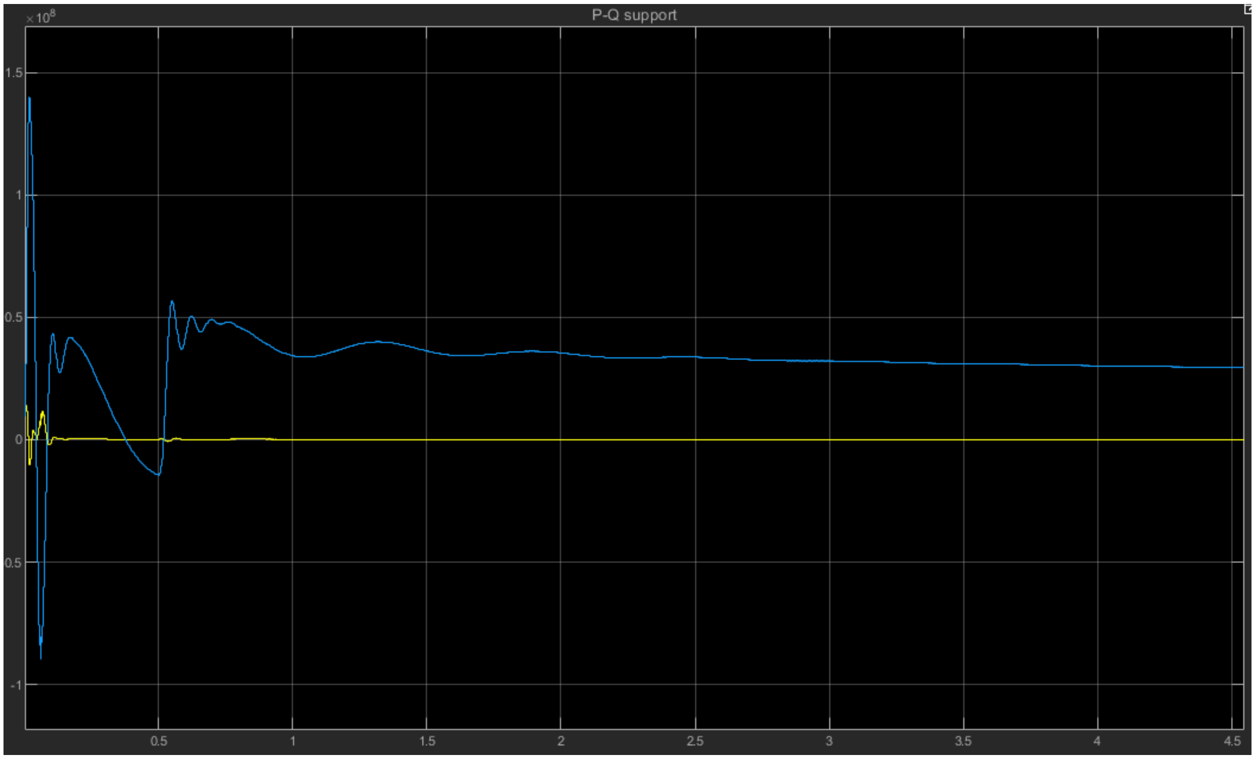
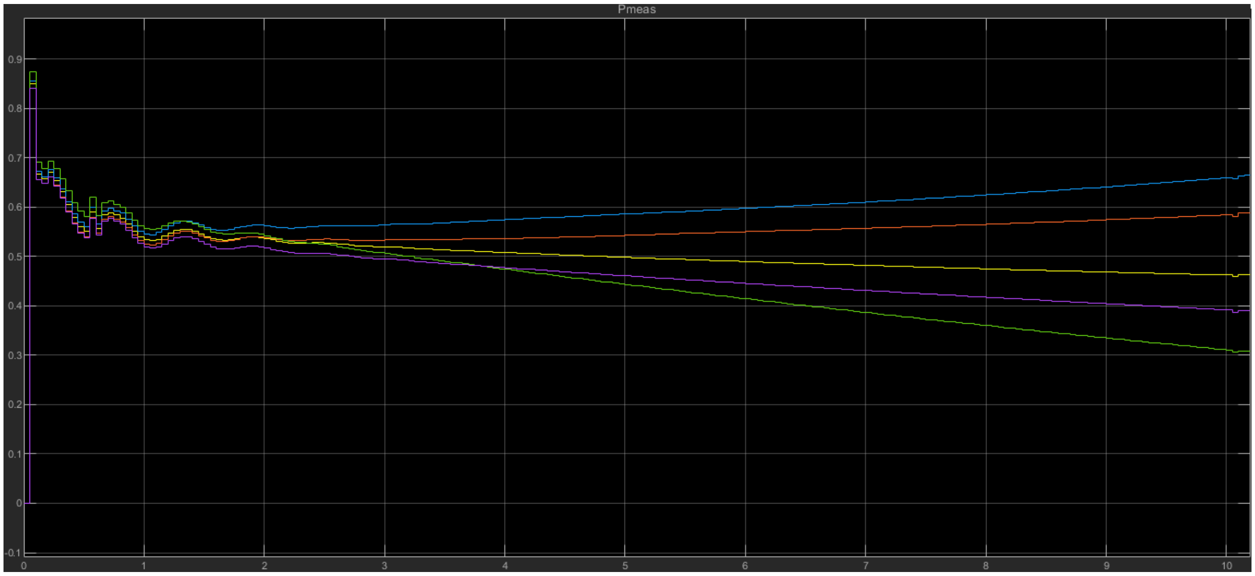
Appendix

Turbine S15 normal operation power output





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