CHAPTER 1
INTRODUCTION

1.1 Background

Global attention is currently focused on the issue of renewable energy development, particularly related to the energy transition as part of efforts to preserve the Earth and ensure the sustainability of living ecosystems[1]. The energy transition is the process of shifting from the use of fossil-based energy sources to renewable energy sources, such as solar, wind, hydro, and geothermal energy [2]. In Indonesia, fossil energy (coal, petroleum, and natural gas) continues to dominate as of 2024, with coal contributing 40.37% of the energy mix, followed by petroleum at 28.82%, natural gas at 16.17%, while the share of new and renewable energy (NRE) only reached 14.65%, which remains far from the targeted 23% by 2025 [3]. To support the shift towards more environmentally friendly and sustainable energy, the Indonesian government has issued various regulations, including Law Number 30 of 2007 on National Energy Management [4], Government Regulation Number 79 of 2014 on the National Energy Policy [5], Presidential Regulation Number 22 of 2017 on the Technical Implementation of the National Energy Policy (KEN) established in Government Regulation Number 79 of 2014 [6]. Presidential Regulation Number 112 of 2022 on the Acceleration of Renewable Energy Development, particularly in the electricity sector [7]. The National Electricity General Plan (RUKN) sets targets for the NRE energy mix, including achieving a 23% contribution from Renewable Energy Technologies (RET) by 2025 and 31% by 2050, reducing greenhouse gas emissions by 29–41% by 2030, and attaining net-zero emissions by 2060 [8].

One of the renewable energies currently being developed and that does not have fuel costs is wind. Wind is air that moves from areas of high air pressure to areas of lower air pressure. Differences in air pressure can cause wind to have physical properties such as speed and direction. Wind speed is the speed of moving air, influenced by differences in elevation, geographical conditions, and the topography of the area [9].

Banyuwangi is one of the easternmost regions of the island of Java. The population growth in the Banyuwangi area, based on Statistics Indonesia (BPS) data, has increased from 1.718.462 people in 2021 to 1.780.015 people in 2023[10]. The annual increase in population can affect the rising energy demand in the Banyuwangi area. The main energy source currently used is fossil energy, which is becoming increasingly limited and has a negative impact on the environment. To support Indonesia's efforts in promoting energy transition and reducing the environmental impact caused by fossil fuels, there is a need for the development of renewable energy, which comes from wind energy sources. This is supported by State Electricity Company (PLN) plan to build a wind power plant in Banyuwangi, which was announced in 2021 [11].

The average wind speed based on BPS data from the last 10 years in the Banyuwangi area is 3.29 m/s, which can reach an average maximum speed of 8 m/s at certain times [12]. The wind speed generated indicates that Banyuwangi has the potential to develop Wind Power Plants (PLTB). This potential is also reinforced by research conducted by Miranda and Sudarti, which explains that the wind speed in Banyuwangi City from April 21–30, 2021, falls into the category of class 4 wind speed (3.4–5.4 knots), making it suitable for use as a source of wind power electricity[6]. However, the varying wind speed, which depends on several factors, can cause intermittent conditions that may disrupt the stability of the electricity supply [13].

The phenomenon of intermittency or sudden fluctuations in wind power supply is one of the most important things in the development of PLTB. Intermittency occurs when wind speed changes drastically in a short period, which can cause the turbine's power output to decrease significantly or even lose its energy supply suddenly. This condition not only affects the performance and efficiency of the turbine but can also affect the stability of the power system as a whole. In line with this, Petersen et al., emphasized that a probabilistic analysis approach is needed to map intermittency risks and develop mitigation strategies according to the characteristics of the power system[14].

Artificial Intelligence (AI) has undergone rapid development. It is widely applied in everyday life, including predicting travel times in Global Positioning Systems (GPS), forecasting weather conditions, detecting certain health conditions, and more. Previous researchers have also explored the application of artificial intelligence in wind speed forecasting. A study by Valdivia-Bautista et al. discusses the use of Artificial Neural Networks (ANN) and hybrid techniques for wind speed prediction. The primary issue addressed is the fluctuation and non-linear nature of wind speed data, which can result in low prediction accuracy when using traditional time series statistical methods. The implementation of ANN, hybrid models (a combination of ANN with other techniques/statistics), as well as preprocessing and noise cancellation techniques (such as wavelet, Empirical Mode Decomposition (EMD), Variational Mode Decomposition (VMD), etc.), is employed to improve prediction accuracy. The performance of ANN methods is compared with hybrid and classical/statistical models using error metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). The results show that hybrid methods produce lower errors compared to other approaches. The advantage of this method lies in its flexibility in capturing complex data patterns. At the same time, its drawbacks include the risk of overfitting and the difficulty of parameter tuning in large datasets [11].

The study by Francisco Diego et al. discusses short-term wind speed prediction using a dynamic ensemble approach that compares random forest, k-nearest neighbors, support vector regression (SVR), and elastic net. The main issue addressed in this research is improving prediction reliability within a 10–60 minute forecasting horizon. The methodology involves using intra-horizon data, ranging from 10 to 60 minutes at 10-minute intervals, and dynamically testing various methods and ensembles. Performance comparisons with other methods are conducted using error metrics such as MAE, MAPE, and RMSE, followed by analysis under noise conditions and extreme weather changes. The results show that the dynamic ensemble outperforms other methods in reducing prediction error. The advantage of this method lies in its robustness to noise and overfitting, while its drawback is the complexity of training time and parameter tuning [12].

The study by Abdul Majid et al. discusses the use of One-Dimensional Convolutional Neural Network (1D CNN) and Bidirectional Long Short-Term Memory (BLSTM) for predicting wind speed at various altitudes. The main issue addressed in the study is the fluctuating and complex nature of wind data, particularly when altitude differences are involved. The methodology employs a 1D CNN for feature extraction, followed by BLSTM to model long-term dependencies in the time series data. Cross-site validation and error visualization were conducted at each altitude level, along with comparisons to individual CNN and BLSTM models to determine which method performs best. The results indicate that the hybrid 1D CNN and BLSTM model outperforms both standalone CNN and BLSTM models. The advantage of this method lies in its capability for multi-step forecasting and handling non-linearity. At the same time, its drawback is the requirement for large datasets and high computational resources [15].

The study by Lei Zhang et al. focuses on wind speed prediction using double time series features, which combine wavelet decomposition, Nonlinear Autoregressive (NAR)/ Nonlinear Autoregressive Exogenous (NARX), and support vector machines (SVM). The primary issue addressed in this research is the accumulation of errors in multi-step-ahead predictions, which often reduces the stability and accuracy of forecasts. The methodology involves preprocessing the data using wavelet decomposition, forecasting with NAR/NARX models, and selecting the best results using an SVM classifier. Experiments were conducted using data from Hohhot, Inner Mongolia, with evaluations on stability and accuracy under various wind fluctuation conditions. The results show that this system is more stable and accurate than conventional multi-step forecasting methods. The advantage of this method lies in its robustness for multi-step forecasting, while its drawback is the increased system complexity and the need for intensive data processing [16].

The study by Merve Ozdemir et al. explores wind speed prediction based on meteorological data using an ensemble neural network, which is based on ANN. The main issue addressed in this research is generating accurate predictions across multiple locations with large datasets and varying site characteristics. The methodology involves developing ANN models with different parameters tailored to each site and integrating them into a single ensemble system. Accuracy comparisons at each site, along with error metrics, are used to evaluate the performance of the proposed approach. The results indicate that the system is robust and accurate even as the number of sites and data volume increase. The advantage of this method lies in its efficiency for multi-site prediction, while its drawback is the requirement for well-standardized input data and complex tuning [17].

The study by J. Sathyraj and V. Sankardoss discusses the use of ensemble deep learning models (Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Recurrent Neural Network (RNN), Gated Recurrent Unit (GRU), and BLSTM) for short-term wind prediction in small wind turbine applications. The main issue addressed in this study is wind variability and the need for accurate predictions to support the operation of small-scale turbines across different seasons and locations. The methodology involves combining multiple deep learning architectures into an ensemble to determine the best-performing combination based on multi-regional data from India. The performance of the study is evaluated through seasonal and site-based segmentation, and accuracy is assessed using metrics such as Mean Square Error (MSE), RMSE, and R^2. The results show that ensemble deep learning models outperform individual methods. The advantage of this approach is its strong generalization ability and high accuracy, while its drawbacks include high computational demands and longer training times [18].

The study by Huang et al. investigates wind prediction using a transformer-based deep learning method. The main issue addressed in this research is the high uncertainty, volatility, and intermittency of wind power output in power systems with high wind farm penetration. The methodology employs a transformer architecture that incorporates self-attention, multi-head attention, residual connections, and a position-wise feed-forward network. Performance evaluation is conducted using metrics such as MSE, MAE, RMSE, and R^2, which are then compared with LSTM and GRU methods. The results indicate that the prediction curve produced by the transformer closely matches the actual curve, and its error metrics outperform those of LSTM and GRU. The advantage of this method lies in its ability to capture long-term dependencies and complex sequential patterns, along with delivering high prediction accuracy. however, it requires significant computational resources [19].

The study by Yunus et al. examines the application of ANN for predicting wind speed in Qaisumah, Saudi Arabia. The main challenge addressed in this study is the development of wind speed forecasting methods to support renewable energy-based power systems in desert areas characterized by fluctuating conditions. The methodology employs a multilayer perceptron (MLP) ANN implemented using MathWorks tools. Performance is evaluated using MSE and MAPE, along with visual plots comparing predicted and actual values. The ANN model is tested with varying numbers of hidden neurons to identify the optimal configuration. The results demonstrate that ANN is highly efficient for long-term nonlinear data forecasting, with prediction curves that closely resemble the actual data. The strengths of this method include its flexibility in modeling nonlinear relationships and its ability to generalize. In contrast, its drawbacks include the need for configuration tuning and the "black-box" nature of the model [20].

Based on a brief review of various previous studies, the development of artificial intelligence methods continues to contribute to improving the accuracy of wind speed predictions. However, each method still has limitations when it comes to forecasting wind time-series data. Therefore, selecting a model that can account for temporal sequences is crucial for obtaining more accurate and robust prediction results.

XLNet is a language processing model that uses an autoregressive pretraining approach or sequential predictions, where each prediction depends on the results of previous predictions. The approach is used to model the discussion by maximizing the logarithmic possibilities of all word sequence permutations and allowing for bidirectional context learning [15]. Therefore, in this study, the XLNet method is used to propose a new solution to overcome the problem and hopefully to propose a solution that achieves state of the art performance in time-series forecasting, particularly in modeling wind speed and direction fluctuations accurately.

1.2 Problem Identification

Based on the background that has been explained, predicting and analyzing wind speed fluctuations is crucial in supporting the development of renewable energy in Banyuwangi. The increasing population growth in this area has led to a growing need for electrical energy, highlighting the need for a reliable and environmentally friendly energy source. Wind energy is one potential solution, but wind speed varies significantly over time.

One of the main challenges in utilizing wind energy is the high variability of wind speed, which can cause sudden changes in wind speed (intermittency) that disrupt the stability of the electric power system and the reliability of energy supply from PLTB. Therefore, wind speed prediction is needed to support the planning and operation of wind power plants in the future. However, predicting wind speed is not an easy task. Conventional models still have limitations in capturing complex and non-linear wind speed change patterns. To answer this challenge, this study proposes the use of XLNet to predict wind speed more accurately based on historical data.

After obtaining the wind speed prediction results, the next step is to conduct a statistical analysis of the predicted data for intermittency. This analysis aims to identify patterns and probabilities of intermittency that can affect the performance of power plants and power systems. Thus, the combination of predictions using XLNet and statistical analysis of intermittency is expected to provide a more comprehensive picture of the potential and challenges of wind energy utilization in Banyuwangi.

1.3 Objective and Contributions

The purpose of this research is to develop wind speed predictions to support the wind power generation needs in Banyuwangi. These projections are expected to aid in planning capacity and efficiency for power plants that rely on renewable energy sources. In addition, this study also aims to formulate the probability of intermittency occurring in the system, thereby reducing the risk of power supply disruptions.

The contribution of this research is to provide benefits to power generation companies in projecting how intermittency occurs and assisting in the selection of the appropriate wind turbine, although this research does not extend to the stage of turbine selection. Additionally, this research contributes a wind speed projection method based on artificial intelligence using the XLNet model, which can academically enrich the approach in wind speed analysis.

1.4 Scope of Work

This study focuses on wind speed projection and intermittent probability analysis in the Banyuwangi area using XLNet. The data used is daily wind speed data during the period April 2020 until March 2021. The data used is only wind speed and direction as input variables, without considering other external factors.

1.5 Expected Result

The expected outcome of this thesis is that the proposed method will provide accurate predictions of wind speed and direction in Banyumas Regency using the XLNet approach. By utilizing historical wind speed data, the model is expected to capture wind fluctuation patterns in the region.

Additionally, statistical analysis of the prediction data is expected to identify and quantify the probability of intermittent events, including the most likely and extreme wind speed changes that can impact the stability of wind power generation.

The evaluation process will utilize performance metrics, including MAE, RMSE, and MAPE, to assess the accuracy of the XLNet model in forecasting wind speed. The results of the analysis are also expected to provide valuable insights into the occurrence and distribution of intermittency, which will be mapped to the wind turbine power curve to better understand its impact on power output stability.

Overall, this research is expected to provide knowledge in the field of renewable energy forecasting, especially in the application of artificial intelligence methods for wind speed prediction and intermittency analysis. These findings are expected to support the planning and development of more reliable wind power plants in Banyuwangi Regency and similar areas.

1.6 Research Methodology

This thesis employs a series of research stages designed within the research methodology. These stages are outlined in several work packages (WPs), which are presented in tabular form, in Table 1.1:

Table 1.1 Work Package of The Research

It	Work Package	Description	Objective
1	Literature Studies and data collection	Learning the theory and concept of wind speed forecasting using artificial intelligence and probability to determine the occurrence of intermittent. Pre-processing data that has been obtained from the plant development team in Banyuwangi, including cleaning, filling in lost data and eliminating anomalies.	Understand wind speed modeling approaches for wind power generation needs. Identify factors that can affect the occurrence of intermittent. Ensure that the data to be used is ready to be used in the next process.
2	Wind speed projection using the XLNet method	Projecting wind speed by training and testing pre-processed data using the XLNet method	Obtaining accurate wind speed projections
3	Intermittent Probability Analysis	Analyze the results of wind speed projections to determine the probability of intermittentity	Understanding the pattern and trend of intermittency in the Banyuwangi area
4	Validation and evaluation	Analyze the results using a predetermined matrix	Ensuring the accuracy and reliability of the XLNet model in predicting wind speed
5	Reporting of research results	Prepare a thesis report that includes methodology, results, analysis, conclusions, and recommendations	Document and write down the process that has been carried out in the research to make an academic contribution

1.7 Structure of Thesis

The following is the structure of this thesis:

- **CHAPTER II: BASIC CONCEPT**
  This chapter presents some basic theory that serves as a foundation for thesis.
- **CHAPTER III: SYSTEM MODEL AND METHOD**
  This chapter presents the system design and experimental methods used in the study.
- **CHAPTER IV: EXPERIMENTAL RESULTS AND ANALYSIS**
  This chapter covers the discussion of experimental results and their analysis.
- **CHAPTER V: CONCLUSION**
  This chapter summarizes the essential findings and conclusions drawn from the research.