CHAPTER 1

INTRODUCTION

This chapter includes the following subtopics, namely: (1) Rationale; (2) Theoretical Framework; (3) Conceptual Framework/Paradigm; (4) Statement of the problem; (5) Hypothesis (Optional); (6) Assumption (Optional); (7) Scope and Delimitation; and (8) Importance of the study.

1.1 Rationale

Electricity is an essential energy source in development and growth projects [4, 46]. Alongside its significance, electricity load forecasting technology continues to evolve and plays a crucial role in the electricity industry [19]. Electricity load forecasting is categorized into long-term , mid-term, and short-term predictions, supporting energy system operations at various levels [4, 10, 30]. Short-term forecasting focuses on predicting energy demand over periods ranging from minutes to a few days ahead, crucial for decision-making in smart grids involving prosumers [4]. Mid-term forecasts span weeks to several months, essential for scheduling power system operations [5]. Long-term forecasts extend over months or years, vital for planning grid maintenance [4, 5]. A key challenge in electricity load forecasting is the variability in energy consumption patterns, leading to concept shift issues due to fluctuations in underlying statistical variables [4]. Therefore, electricity load forecasting greatly aids in optimizing planning processes in power generation industries [14, 46]. Additionally, external factors such as consumer trends and weather characteristics significantly impact the linearity and predictability of electricity demand.

External factors, such as consumer trends and weather characteristics, significantly impact the linearity and predictability of electricity demand. These factors, especially weather conditions, introduce complexity, nonlinearity, and instability into electricity demand [6]. Incorporating weather parameters such as humidity, irradiance, precipitation, temperature, wind speed, and solar irradiation is crucial for planning electricity systems and accurately estimating demand over both short-term and long-term periods [3]. Studies conducted at regional and national levels, including in the United States [40], Saudi Arabia [29], and Turkey [2], underscore the significant impact of these parameters on electricity load forecasting [3, 37]. Therefore, understanding and analyzing these weather parameters, along with consumer trends, are essential steps in developing more precise and effective forecasting models that can adapt to varying geographical conditions and enhance overall reliability in electricity supply planning.

The need to address these external factors has driven technological advancements and the development of various approaches and algorithms for electricity load forecasting.

These methods can generally be divided into two main categories, which are statistical models and machine learning models [25, 43]. Statistical models such as Autoregressive Moving Average (ARIMA) [37], Seasonal ARIMA (SARIMA) [9], Linear Regression [22], Multiple Linear Regression (MLR) [31] have been popularly used for electricity load forecasting. Machine learning models such as Support Vector Machine (SVM) [38], Artificial Neural Networks (ANN) [38], and Gaussian Processes (GP) have also been widely adopted [31].

Several studies have applied machine learning models to predict short-term electricity load in the future. For instance, Wu et al. (2023) forecasted short-term electricity load in the United States using a BiLSTM hybrid prediction models with trend feature extraction [40]. In Mbuli et al. (2020), the most common methods were Back Propagation Neural Network (BPNN) and SVM. However, these methods do not consider time series correlations, and there are issues with effectively handling large training samples [27, 31]. A Convolutional Neural Network (CNN) is a machine learning models typically used for accurate short-term electricity load forecasting. This models has lower complexity and fewer learnable parameters, making it more effective for electricity load forecasting [2, 34]. Therefore, more efficient CNN models have been developed to electricity load forecasting accurately.

Research by Maryan Imani et al. [15] indicates that CNN Temperature Load is more accurate in predicting household electricity load compared to previous methods such as NRE, FFNN, LSTM, SVR, and SARIMA. Additionally, Kuihua Wu's study [41] shows that employing Attention Mechanism in CNN-LSTM-BiLSTM models enhances the performance of electricity load forecasting. The Attention Mechanism assigns varying weights to input features, giving higher weight to more relevant inputs and lower weight to less relevant ones. This enhancement contributes to better accuracy and performance in predicting electricity usage within integrated energy systems for short-term forecasting. However, the complexity of these models can pose challenges in practical applications. Therefore, to address these complexities, signal decomposition techniques are required to reduce data complexity and dimensionality, improve models stability and accuracy, and capture nonlinear and non-stationary data features [45].

Some researchers have explored various signal decomposition techniques such as Discrete Fourier Transform (DFT), Short Time Fourier Transform (STFT), and Fast Fourier Transform (FFT) to compare time and frequency representations of input signals effectively [12, 28]. However, these methods have shown limited accuracy in analyzing unstable and nonlinear signals [12, 16, 32]. Therefore, the Empirical Mode Decomposition (EMD) signal models was proposed. EMD has been widely adopted in forecasting electricity demand due to its capability to handle nonlinear and non-stationary signals, effectively capturing their time, frequency, and energy characteristics [5, 17, 32]. EMD decomposes signals into intrinsic mode function (IMFs) components, adaptively capturing complex signal characteristics evolving over time [11, 12, 32]. Despite the advantages of EMD, the selection of appropriate IMFs remains a challenge. The performance of prediction models can be significantly affected by suboptimal IMFs selection. Therefore, it is essential to develop a systematic framework for selecting the most relevant IMFs. Such a framework would ensure that only the most informative components are utilized in feature extraction, thereby improving the overall accuracy and effectiveness of prediction models.

In this paper, we propose a machine learning approach to electricity load forecasting by combining CNN with an Attention Mechanism, leveraging time feature modeling to observe consumer trends and weather characteristics. To achieve optimal accuracy, we further develop additional features using EMD within a framework for selecting IMFs as part of feature extraction. Our case study in the East Java area, Indonesia, demonstrates the effectiveness of this approach, showcasing the significance of the Attention Mechanism in CNN and the critical role of IMFs selection frameworks within the EMD process in improving prediction models.

1.2 Statement of the Problem

Predicting electricity load is crucial in modern decentralized power systems as it helps anticipate the expected electrical load for specific durations [39, 44]. This capability is essential for effectively planning and managing electricity supply to meet community needs. In East Java, predicting electricity loads has become more intricate due to factors such as urban and industrial development, climate change, and population growth [12].

This research focuses on predicting weather-based electrical loads in East Java using CNN with Attention Mechanism as a machine learning model, in combination with a signal decomposition approach using EMD. This approach was chosen to address the variability and complexity of data inherent in predicting electric loads [16, 23]. EMD is employed to extract detailed signal components [12, 28], while CNN efficiently extracts features from each signal component to accelerate computation time [26, 31, 44]. The Attention Mechanism assigns weights to each feature to enhance accuracy and reduce data analysis time [15].

The primary research question addressed in this study is:

How to design an electricity load forecasting system based on weather data and time by integrating CNN with an Attention Mechanism and subsequently using EMD to decompose the load signal into IMFs to further improve forecasting performance?

1.3 Objective and Hypotheses

In this section, we outline the primary objectives and hypotheses of the study.

1.3.1 Objective

The objective of this research is to develop an accurate electricity load forecasting system by integrating CNN with an Attention Mechanism and using EMD to enhance prediction performance. Specifically, this research aims to:

1. Evaluate the accuracy of CNN combined with an Attention Mechanism for forecasting electricity load, leveraging weather data and time features.

2. Apply EMD for feature extraction, focusing on decomposing the load signal into IMFs and identifying the most significant IMFs to improve the accuracy of the forecasting model.

1.3.2 Hypothesis

The hypothesis of this research is that integrating CNN with an Attention Mechanism, along with EMD for feature extraction, will significantly improve the accuracy of electricity load forecasting. Specifically, it is hypothesized that:

1. Combining CNN with an Attention Mechanism will enhance the accuracy of electricity load forecasting by leveraging weather data and time features.

2. Applying EMD to decompose the electricity load signal into IMFs and selecting the most relevant IMFs for feature extraction will further enhance the accuracy of the forecasting model by providing a more detailed signal representation.

1.4 Assumption

This study assumes that electricity demand patterns in East Java exhibit seasonal variations influenced by weather conditions and consumer behavior. It is assumed that the selected weather parameters, such as temperature, humidity, irradiance, precipitation, wind speed, and solar irradiation, adequately represent the external factors affecting electricity load and that their integration as input features will enhance forecast accuracy. Additionally, the use of CNN with an Attention Mechanism and EMD is widely accepted in the literature for handling nonlinear and non-stationary data characteristics in time series forecasting.

1.5 Scope and Delimitation

This study focuses on examining the accuracy of short-term electricity load forecasting, with weather parameters (humidity, irradiance, precipitation, temperature, wind speed, solar irradiation), time features, and consumer behavior trends as key independent variables. The study is specifically conducted in East Java, Indonesia, chosen for its diverse industrial and consumer activities that significantly impact electricity demand patterns. The timeframe of the study encompasses short-term forecasting periods, ranging from hours to a few days ahead. The inclusion of weather parameters is justified due to their direct influence on electricity consumption patterns and their inherent variability. Time-related features are included to capture daily and weekly consumption patterns influenced by factors such as peak hours and weekdays. Additionally, analyzing trends in consumer behavior aids in understanding shifts in demand attributable to societal and economic factors.

1.6 Significance of the Study

This study presents a novel method for short-term electricity load forecasting in East Java, Indonesia, by integrating CNN with an Attention Mechanism and utilizing EMD to decompose the load signal into IMFs. This innovative approach aims to enhance forecasting accuracy by incorporating weather parameters and time features, which are crucial for effective energy management and infrastructure planning.