ANALYSIS OF FORECAST OF RENEWABLE ENERGY DEVELOPMENT IN NORTH SUMATRA USING ANFIS

Yoga Tri Nugraha[1,2], Puan Maharani Simanjuntak[3], Muhammad Irwanto[4], Rizkha Rida[5], M.A. Othman[6]

[1)] Department of Electrical Engineering, Universitas Al-Azhar Medan, Medan, Indonesia
[2,3,4]) Department of Electrical Engineering, Universitas Prima Indonesia, Medan, Indonesia
[5]) Department of Electrical Engineering, Universitas Darma Agung, Medan, Indonesia
[6]) Department of Electronic Engineering, Universiti Teknikal Malaysia Melaka, Melaka, Malaysia
Email: yogatrinugraha16@gmail.com, 193303020201@unprimdn.ac.id, muhammadirwanto@unprimdn.ac.id, rizkharida26@gmail.com, azlishah@utem.edu.my

Info Artikel

Article history:
Received Mar 23, 2024
Revised Apr 03, 2024
Accepted Apr 30, 2024

ABSTRACT

The transition towards renewable energy sources is critical for sustainable development, particularly in regions like North Sumatra, Indonesia, where energy demand is increasing rapidly. This research presents an analysis of the forecast of renewable energy development in North Sumatra using the ANFIS. The analysis begins with data collection and preprocessing, incorporating historical data on energy consumption, renewable energy installations, population growth, economic indicators, and environmental factors. ANFIS models are then developed and optimized to capture the complex relationships between these variables and forecast renewable energy trends accurately. Model validation and performance evaluation techniques ensure the reliability of the forecasted outcomes. The results of the calculations conducted using the ANFIS method obtained an error value of 0,000201092% and has a Forecast of Renewable Energy Development in North Sumatra in 2028 of 160.44 MW.

Keywords: *Renewable Energy Development, ANFIS, North Sumatra*

This is an open access article under the CC BY-SA License

Corresponding Author:
Yoga Tri Nugraha,
Department of Electrical Engineering, Faculty of Engineering
Universitas Al-Azhar Medan,
Pintu Air IV Street No. 214 Medan, North Sumatra, Indonesia.
Email: yogatrinugraha16@gmail.com

1. INTRODUCTION

Renewable energy development holds significant promise for North Sumatra, Indonesia, as the region seeks sustainable solutions to meet its growing energy demand while mitigating environmental impacts. In this context, the analysis of forecasted renewable energy development using the Adaptive Neuro-Fuzzy Inference System (ANFIS) emerges as a vital tool for policymakers, energy planners, and stakeholders to anticipate future trends and make informed decisions. This introduction sets the stage by providing an overview of the importance of renewable energy, the challenges faced, and the relevance of ANFIS in addressing these challenges[1][2].

Like many other places in the world, North Sumatra must simultaneously meet the growing need for energy while lowering greenhouse gas emissions. As a sustainable substitute for fossil fuels, renewable energy sources support economic expansion, environmental protection, and energy security. Harnessing the abundant renewable resources in North Sumatra, including solar, wind, hydroelectric, geothermal, and biomass, presents a pathway towards a cleaner and more resilient energy future[3][4].

Forecasting renewable energy development poses several challenges due to the inherent variability of renewable resources, technological advancements, policy changes, and economic factors. Traditional forecasting methods often struggle to capture the nonlinear and uncertain nature of renewable energy data, highlighting the need for advanced modelling techniques. ANFIS, with its ability to integrate fuzzy logic principles with neural networks, offers a promising approach to address these challenges by modelling complex relationships and making accurate predictions[5].

ANFIS has gained popularity in various fields, including energy forecasting, due to its ability to handle nonlinear data and uncertainties effectively[6]. By combining the strengths of neural networks and fuzzy logic, ANFIS can capture the intricacies of renewable energy systems and provide reliable forecasts. In the context of North Sumatra, where renewable energy adoption is expected to play a crucial role in the energy transition, ANFIS offers a valuable tool for policymakers and stakeholders to anticipate future energy scenarios, optimize resource allocation, and support sustainable development initiatives[7].

2. RESEARCH METHOD

2.1 Research Flow Diagram

The flow diagram outlines the main steps involved in conducting this research, as seen in Figure 1.

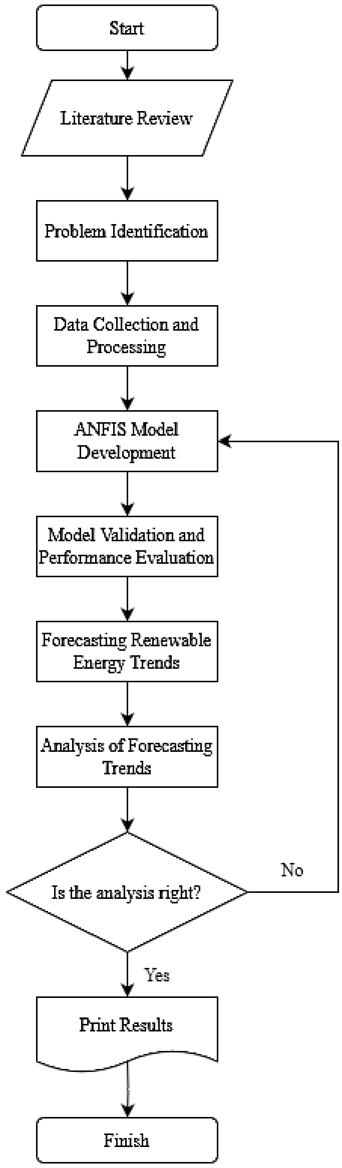

Figure 1 Research Flow Diagram

2.2 ANFIS

The adaptive neural network and fuzzy logic explanatory powers are combined in the Adaptive Neuro-Fuzzy Inference System, a hybrid intelligent system. The main ideas and elements of ANFIS are broken down as follows:

1. Fuzzy Logic

a. Fuzzy logic provides a framework for dealing with uncertainty and imprecision in data by allowing for gradual transitions between true and false values[8].

b. Fuzzy logic employs linguistic variables, fuzzy sets, and fuzzy rules to model human-like reasoning.

c. Linguistic variables represent input and output variables in natural language terms (e.g., "low," "medium," "high").
d. Fuzzy sets define the membership functions that map numerical values to degrees of membership in linguistic terms.

2. Neural Networks
a. Computational models called neural networks are based on the architecture and operations of the human brain [9].
b. They are made up of linked nodes (neurons) arranged in layers, which include hidden, output, and input layers [10].
c. Neural networks learn from data through a process known as training, adjusting the weights between neurons to minimize prediction errors.

3. ANFIS Architecture[11]
a. ANFIS combines the concepts of fuzzy logic and neural networks to create a hybrid system for modelling and inference[12].
b. It typically consists of five layers:
   i. Layer 1: Input layer, which receives crisp input data.
   ii. Layer 2: Fuzzy layer, where the supplied data is subjected to fuzzy membership function applications.
   iii. Layer 3: Fuzzy rule layer, which computes the degree of firing for each fuzzy rule.
   iv. Layer 4: Normalization layer, This makes the rules' firing strengths more normal.
   v. Layer 5: Output layer, where a weighted sum of the normalized firing strengths is used to calculate the final output.

4. Learning Algorithm
   a. Usually, gradient descent and least squares techniques are used to create the learning algorithm utilized in ANFIS [13].
   b. It adjusts the parameters of the fuzzy membership functions and the neural network weights to minimize the error between the predicted and actual outputs.
   c. The learning process involves forward propagation of inputs through the network, followed by backward propagation of errors to update the parameters.

5. Training and Optimization
   a. ANFIS models are trained using a dataset containing input-output pairs.
   b. During the training phase, the model's parameters are changed to minimise a selected objective function, like mean squared error.
   c. Iterated updates to the model parameters are made using optimization techniques like gradient descent or its variations until convergence.

6. Inference and Prediction
a. Once trained, ANFIS models can perform inference and make predictions based on new input data[14].
b. The input data are fuzzified using the membership functions defined during training, and the fuzzy rules are applied to compute the output.
c. ANFIS provides a mechanism for combining the interpretability of fuzzy logic with the learning capabilities of neural networks, making it well-suited for applications such as system modelling, control, and prediction[15].

Overall, ANFIS offers a flexible and powerful approach to modelling complex systems with uncertain or nonlinear relationships, making it widely used in various fields, including engineering, finance, and pattern recognition[16].

2.3 Renewable Energy

Energy that comes from naturally replenishing sources that don't run out while being used is referred to as renewable energy. When burned, fossil fuels like coal, oil, and natural gas are limited resources that contribute to pollution and climate change. In contrast, renewable energy sources are plentiful and emit little to no greenhouse gases when they generate energy. Several prevalent forms of sustainable energy include:

1. Solar Energy: Solar energy is obtained from sunlight, which can be converted into electricity using photovoltaic (PV) cells or concentrated solar power (CSP) systems. Solar energy is abundant and widely available, making it one of the fastest-growing sources of renewable energy globally.
2. Wind Energy: Wind energy is harnessed by wind turbines, which convert the kinetic energy of the wind into electricity. Wind power is a mature technology and is utilized in onshore and offshore wind farms to generate electricity at scale.
3. Hydropower: Hydropower, also known as hydroelectric power, harnesses the energy of flowing water to generate electricity. It is one of the oldest and most widely used forms of renewable energy, with large-scale hydropower plants providing a significant portion of the world's electricity.
4. Biomass Energy: Biomass energy is derived from organic materials such as wood, crop residues, and organic waste. Biomass can be burned directly for heat or electricity generation, converted into biofuels like ethanol

and biodiesel, or processed into biogas through anaerobic digestion.

5. Geothermal Energy: Geothermal energy produces electricity or heat and cools by harnessing heat from the Earth's interior. Geothermal power plants use hot water or steam that is stored underground to turn turbines and generate electricity.
6. Tidal and Wave Energy: The kinetic energy of ocean waves and tides is captured by tidal and wave energy, which produces electricity. Although they are still in their infancy, wave and tidal energy technologies have the potential to offer coastal areas a reliable and regular source of renewable energy.

Renewable energy offers numerous benefits compared to fossil fuels, including:

1. Environmental Sustainability: Because renewable energy sources emit little or no greenhouse gases or air pollutants, they have a positive environmental impact and help mitigate climate change.
2. Energy Security: Because renewable energy sources are plentiful and widely available, there is less need to import fossil fuels, improving energy security.
3. Economic Opportunities: The renewable energy sector boosts economic growth, generates employment, and encourages technological and manufacturing innovation.
4. Resource Diversity: Unlike fossil fuels, which are concentrated in specific regions, renewable energy sources are diverse and can be deployed locally, promoting energy independence and resilience.

The transition to renewable energy is a key strategy for addressing climate change, promoting sustainable development, and ensuring a clean and secure energy future. However, it also requires overcoming various challenges, including intermittency, grid integration, technological advancements, policy support, and investment in infrastructure. By accelerating the adoption of renewable energy technologies and fostering a supportive policy and regulatory environment, societies can unlock the full potential of renewable energy to meet their energy needs while safeguarding the planet for future generations.

2.4 Forecast

Predicting or estimating future trends, events, or results based on historical and current data is the process of forecasting. It is a crucial instrument utilized in many domains, such as supply chain management, business, finance, economics, and meteorology, as well as general decision-making. The primary goal of forecasting is to reduce uncertainty and assist decision-makers in planning, budgeting, resource allocation, and risk management. Key aspects of forecasting include:

1. Data Collection: The first step in forecasting involves gathering relevant data, which may include historical records, market data, economic indicators, weather patterns, customer demand, or any other information that influences the phenomenon being forecasted.
2. Analysis and Modeling: Following collection, data is examined to find trends, patterns, and connections. To create forecasting models that capture the underlying structure of the data, statistical techniques like time series analysis, regression analysis, exponential smoothing, and machine learning algorithms are employed.
3. Extrapolation and Interpolation: Forecasting techniques may involve extrapolating past trends into the future to make predictions or interpolating values between known data points. These methods are commonly used in time series forecasting when historical data is available.
4. Judgmental Forecasting: In some cases, forecasting relies on the expertise and judgment of individuals or groups to make predictions based on qualitative information, expert opinions, market research, or consensus estimates. This approach is often used when historical data is limited or unreliable.
5. Forecast Evaluation: Forecast accuracy is assessed by comparing predicted values to actual outcomes. Various metrics, such as Mean Absolute Error (MAE), Mean Squared Error (MSE), forecast bias, and forecast skill scores, are used to evaluate the performance of forecasting models and identify areas for improvement.
6. Uncertainty and Risk Management: Forecasting acknowledges that all predictions involve uncertainty and risk. Techniques such as scenario analysis, sensitivity analysis, and probabilistic forecasting are used to quantify and manage uncertainty, allowing decision-makers to consider multiple possible outcomes and their associated probabilities.
7. Continuous Improvement: Forecasting is an iterative process that requires continuous monitoring, evaluation, and adjustment based on new data and changing circumstances. Feedback loops help refine forecasting models and improve their accuracy over time.

All things considered, forecasting gives decision-makers insightful knowledge about future trends and circumstances, empowering them to foresee changes, deploy resources wisely, spot opportunities, and reduce risks. While no forecasting method can predict the future with absolute certainty, a well-designed and well-executed forecasting process can enhance decision-making and contribute to organizational success. Forecasting can be categorized into several types based on various criteria, such as data characteristics, time horizon, techniques used, and application domain. Here are some common types of forecasting:

a. Time Series Forecasting: Time series forecasting is the process of projecting a variable's future values using its historical observations, which are usually arranged chronologically. When data points are gathered on a daily, monthly, or annual basis throughout time, this kind of forecasting is employed. Seasonal decomposition, exponential smoothing, and Autoregressive Integrated Moving Average (ARIMA) are some time series forecasting techniques.
b. Causal or Regression Forecasting: Regression or causal forecasting is the process of projecting a variable's future values based on the correlation it has with one or more predictor variables. When there is an obvious cause-and-effect link between variables, this kind of forecasting is frequently employed. One method that's frequently utilized in causal forecasting is regression analysis.
c. Qualitative Forecasting: To predict future events, qualitative forecasting makes use of expert judgement, subjective evaluations, and opinions. When there is a lack of available, faulty, or restricted historical data, this kind of forecasting is employed. The Delphi method, scenario analysis, market research, and expert opinion polls are examples of qualitative forecasting methodologies.
d. Quantitative Forecasting: Using statistical and mathematical methods, quantitative forecasting makes predictions about the future based on past performance. When previous data is available and can be examined to find patterns and trends, this kind of forecasting is appropriate. Regression analysis, machine learning algorithms, and time series analysis are examples of quantitative forecasting methodologies.
e. Short-Term and Long-Term Forecasting: Forecasting can also be classified based on the time horizon of the predictions. Short-term forecasting typically predicts outcomes within a relatively short time frame, such as days, weeks, or months, while long-term forecasting predicts outcomes over a longer time horizon, ranging from months to years or even decades.
f. Demand Forecasting: The goal of demand forecasting is to project future consumer demand for goods and services. Supply chain optimization, production scheduling, and inventory management all depend on it. Time series analysis, regression analysis, market research, and predictive analytics are some of the methods used in demand forecasting.
g. Financial Forecasting: Predicting future financial performance, including sales revenue, earnings, cash flow, and stock prices, is known as financial forecasting. It is essential for risk management, investment decisions, financial planning, and budgeting. Time series analysis, regression analysis, discounted cash flow analysis, and financial modelling are some of the methods used in financial forecasting.
h. Weather Forecasting: Weather forecasting predicts future weather conditions, such as temperature, precipitation, wind speed, and humidity. It is essential for agriculture, transportation, energy management, disaster preparedness, and public safety. Weather forecasting techniques include numerical weather prediction models, satellite imagery, radar data analysis, and statistical forecasting models.

These are just a few examples of the different types of forecasting used in various fields and applications. The choice of forecasting type depends on the nature of the data, the objectives of the forecast, the availability of historical data, and the specific requirements of the application domain. Forecasting renewable energy development involves predicting future trends, capacities, and adoption rates of renewable energy technologies. Several factors influence the accuracy and reliability of such forecasts:

a. Policy and Regulations: Government policies, incentives, subsidies, and regulatory frameworks significantly influence the development and deployment of renewable energy technologies. Changes in policies, such as renewable energy targets, carbon pricing mechanisms, feed-in tariffs, and renewable energy mandates, can impact investment decisions and the pace of renewable energy development.
b. Technological Advancements: Technological developments in renewable energy can reduce costs, increase efficiency, and hasten adoption. Examples of these developments include advancements in solar Photovoltaics (PV), wind turbines, energy storage systems, and grid

integration technologies. Technological advancements and their possible effects on the market for renewable energy must be taken into consideration while forecasting.

c. Economic Factors: Economic factors, including the cost competitiveness of renewable energy compared to conventional energy sources (e.g., coal, natural gas), access to financing, interest rates, and global economic conditions, influence investment decisions and the rate of renewable energy deployment. Forecasts need to consider the economic viability and attractiveness of renewable energy projects.

d. Energy Market Dynamics: Energy market dynamics, such as electricity demand growth, energy market prices, grid stability, and capacity factors, affect the integration of renewable energy into the existing energy infrastructure. Forecasts should account for market trends, demand-supply dynamics, and the evolving energy landscape.

e. Environmental Considerations: Greenhouse gas emissions, air quality, and environmental sustainability are the main factors driving the use of renewable energy technologies. Forecasts must take into account public perceptions of sustainability, environmental policies, and the possible effects of environmental laws on the growth of renewable energy sources.

f. Resource Availability: The availability and variability of renewable energy resources, such as solar irradiance, wind speed, hydrological conditions, biomass availability, and geothermal heat, influence the feasibility and potential of renewable energy projects in different regions. Forecasts must account for resource availability and variability when assessing the renewable energy potential of specific locations.

g. Infrastructure and Grid Integration: The availability and adequacy of infrastructure, including transmission and distribution networks, grid stability measures, energy storage facilities, and smart grid technologies, affect the integration of renewable energy into the grid. Forecasts should consider grid capacity, infrastructure investments, and grid modernization efforts needed to accommodate increased renewable energy penetration.

h. Market and Industry Dynamics: Market trends, competitive landscape, supply chain dynamics, industry collaborations, and investment trends in the renewable energy sector influence the pace and direction of renewable energy development. Forecasts need to consider market dynamics, industry partnerships, and emerging business models shaping the renewable energy market.

i. Social and Cultural Factors: Social acceptance, community engagement, cultural attitudes towards renewable energy, and public awareness campaigns influence the deployment of renewable energy projects. Forecasts should consider social factors and stakeholder engagement strategies to address community concerns and promote renewable energy adoption.

j. Global Trends and Geopolitical Factors: Global trends, geopolitical dynamics, international agreements (e.g., Paris Agreement), energy security concerns, and geopolitical tensions impact the global energy landscape and renewable energy development. Forecasts need to consider geopolitical risks, energy geopolitics, and global cooperation efforts in the renewable energy sector.

Taking into account these factors and their interactions is essential for developing accurate and insightful forecasts of renewable energy development. Integrated modelling approaches, scenario analysis, sensitivity analysis, and stakeholder engagement can help enhance the robustness and reliability of renewable energy forecasts.

2.5 Population

The total population refers to the entire number of individuals residing in a specific geographic area, such as a country, region, city, or other defined area. It is a fundamental demographic indicator and is typically measured at a specific point in time or over a particular period, such as a year. The total population can vary significantly across different regions and countries due to factors such as birth rates, death rates, migration patterns, economic conditions, social policies, and cultural factors.

Population data is essential for various purposes, including policy planning: governments and policymakers use population data to plan and implement policies related to education, healthcare, infrastructure, housing, social services, and economic development; resource allocation: population data informs resource allocation decisions, such as distributing funding for public services, determining electoral representation, and allocating government assistance programs; market analysis: businesses and marketers use population data to analyze consumer demographics, identify target markets, and make informed decisions about product development, marketing strategies, and market expansion; healthcare planning: population data is used to assess healthcare needs, plan healthcare services, allocate healthcare resources, and monitor public health trends, including disease prevalence, vaccination coverage, and healthcare access; urban planning: urban planners use population data to assess population growth, analyze housing demand, plan transportation systems, manage land use, and develop sustainable urban infrastructure; academic research: researchers in various fields, including sociology, economics, geography, public health, and environmental studies, use population data to study demographic trends, analyze social dynamics, and investigate the impacts of population changes on society and the environment.

The total population is typically measured through national censuses, demographic surveys, population registers, and administrative records maintained by government agencies and international organizations. Population estimates and projections are regularly updated to reflect changes in population size, composition, and distribution over time.

2.6 Economic

An economy's ability to produce more goods and services over time is referred to as economic growth. Usually on an annual basis, it is quantified as the percentage change in real Gross Domestic Product (GDP) or Gross National Product (GNP) from one period to the next. Raising living standards, decreasing poverty, and enhancing population well-being all depend on economic growth. It makes increased access to goods and services, increased work prospects, and higher salaries possible. Economic growth is influenced by a number of factors, including:

1. Investment in physical and human capital: This includes investments in infrastructure, technology, education, and healthcare, which enhance productivity and efficiency.
2. Technological progress: Advances in technology lead to increased productivity, innovation, and the development of new industries and products.
3. Natural resources: Access to and efficient utilization of natural resources can drive economic growth, although reliance solely on natural resources can lead to volatility and sustainability challenges.
4. Institutional factors: Stable political institutions, effective governance, and supportive regulatory environments can foster economic growth by providing a conducive environment for business development and investment.
5. Trade and globalization: By creating new markets, encouraging specialization, and easing the movement of capital, goods, and services across borders, trade can boost economic growth.

The objective of sustainable economic growth is to maintain long-term prosperity and well-being for present and future generations by striking a balance between economic expansion, environmental protection, and social equality.

2.7 Fossil Fuel Usage

The use of fossil fuels, which are hydrocarbon-based resources created from the remnants of extinct plants and animals, to generate energy is known as fossil fuel usage. The three main types of fossil fuels are natural gas, coal, and oil (petroleum). For many years, these fuels have dominated the energy landscape, providing energy for industrial processes, heating, transportation, and electricity generation. Here are some key points about fossil fuel usage:

1. Electricity Generation: Fossil fuels have historically been the primary sources of electricity generation in many countries around the world. Coal in particular has been widely used in power plants, although there has been a shift towards natural gas and renewable energy sources in recent years due to environmental concerns and economic factors.
2. Transportation: Petroleum products such as gasoline and diesel fuel dominate the transportation sector, powering cars, trucks, ships, and airplanes. While there have been efforts to promote alternative fuels and electric vehicles to reduce dependence on fossil fuels in transportation, they still play a significant role.
3. Heating and Cooling: Fossil fuels are commonly used for heating buildings and water in residential, commercial, and industrial settings. Oil and natural gas are often used in furnaces and boilers for space heating, while petroleum-based products like propane are used in areas where natural gas pipelines are not available.
4. Industrial Processes: Fossil fuels are integral to various industrial processes, including manufacturing, chemical production, and refining. They serve as feedstocks for plastics, fertilizers, pharmaceuticals, and other products, as well as providing energy for operations.

3. RESULT AND DISCUSSION

Table 1 displays the data that were used in this research.

Table 1. Forecast Data for ANFIS Testing

Year	Population (Million people)	Economy (GRDB) (Trillion)	Fossil Fuel Usage	Renewable Energy Development (MW)
2018	14.41	512.76	5.15	71.5
2019	14.56	539.51	6.22	80.3
2020	14.70	533.74	6.29	89.1
2021	14.93	547.65	7.01	97.4
2022	15.11	573.52	7.89	100.6

From Table 1 above will be inserted into ANFIS data for data training and data testing. Then it will be produced in the form of the ANFIS structure result shown in Figure 2.

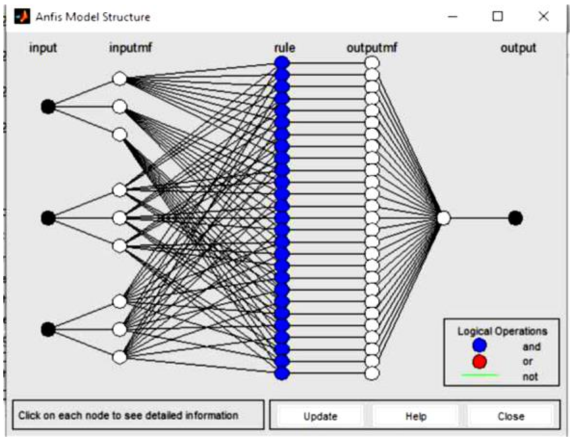

Figure 2. ANFIS Structure

Figure 2 above shows that ANFIS generates node 78, linear parameter number 27 and nonlinear parameters number 27, parameter total number 54, training data pair number 5, verification data number 0 and Fuzzy rule number 27. So it produces the fuzzy rule shown in Figure 3.

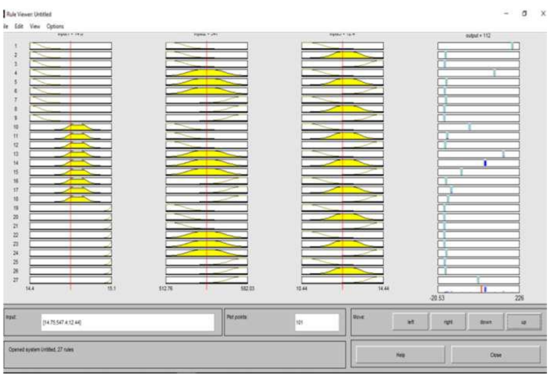

Figure 3. Fuzzy Rule

The fuzzy rule depicted in Figure 3 demonstrates that testers of renewable energy forecast data in North Sumatra have created 53 rules. Out of the 53 rules that fuzzy generated, one rule found in the 41st fuzzy rule has the correct answer. Figure 4 illustrates the error (RMSE) of 0,000201092% at the time of data training.

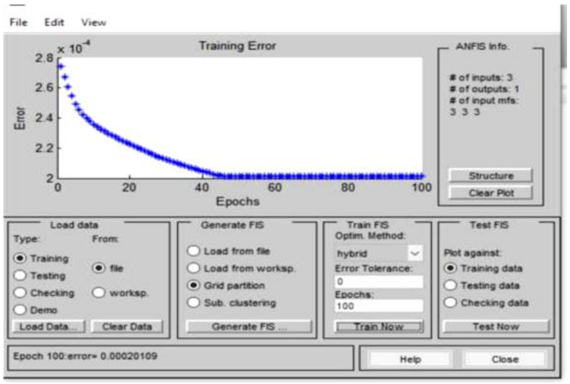

Figure 4. Training Data Error Result

After conducting data training on ANFIS that produces a small error value, the next test of ANFIS data is performed, which can be seen in Figure 5.

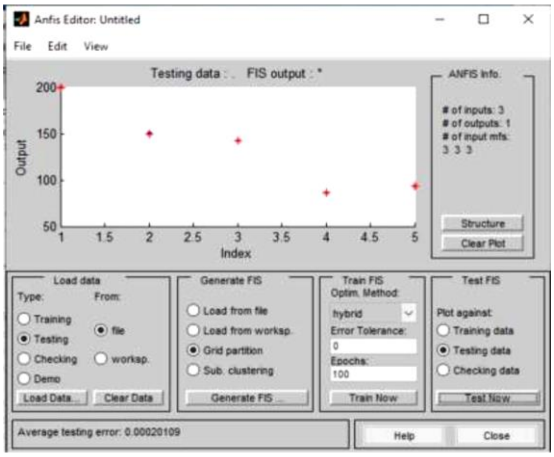

Figure 5. Testing Data Error Result

The ANFIS produced an RMSE value of 0,000201092% of the real data, as seen in Figure 5 above. Table 2 thus shows a comparison of the forecasted results utilising ANFIS with the actual data in PLN.

Table 2. The Results of The Forecast Using ANFIS With Actual Data of PLN

Year	Forecast of Renewable Energy Development Using ANFIS (MW)	Actual Data of PLN (MW)
2022	100.5	100.6
2023	107.21	108.1
2024	161.87	162.01
2025	165.29	168.88

2026	157.21	161.19
2027	158.31	163.2
2028	160.44	166.8

Table 2 above is a comparison between ANFIS and actual data, for it will be formed using the graph in Figure 6.

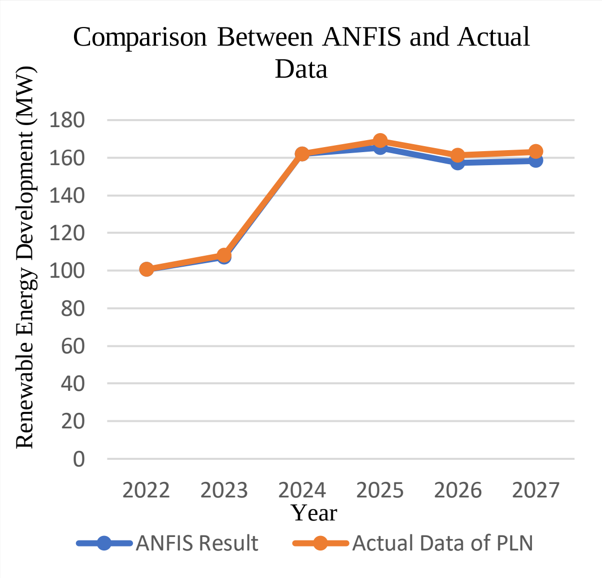

Figure 6. Comparison Between ANFIS And Actual Data

4. CONCLUSION

Renewable energy has great potential to meet the world's energy needs sustainably, mitigate environmental impacts, and strengthen global energy resilience. However, to a successful energy transition, it requires collaboration between governments, communities, and international institutions, as well as a continuous focus on technological innovation and supportive policies. This research focuses on the forecast of renewable energy in North Sumatra. The results of the calculations conducted using the ANFIS method obtained an error value of 0,000201092% and has a Forecast of Renewable Energy Development in North Sumatra in 2028 of 160.44 MW.

REFERENCES

[1] R. T. Ginting, Y. Tri Nugraha, D. Perangin-Angin, T. T. Gultom, W. P. Nainggolan, and D. Sitanggang, "Short-Term Forecast for the Growth of Indonesia'S New Renewable Energy Using the Adaptive Neuro-Fuzzy Inference System," *J. Sist. Inf. dan Ilmu Komput. Prima(JUSIKOM PRIMA)*, vol. 6, no. 2, pp. 57–60, 2023, doi: 10.34012/jurnalsisteminformasidanilmukomputer.v6i2.3477.

[2] C. Ghenai, O. A. A. Al-Mufti, O. A. M. Al-Isawi, L. H. L. Amirah, and A. Merabet, "Short-term building electrical load forecasting using adaptive neuro-fuzzy inference system (ANFIS)," *J. Build. Eng.*, vol. 52, p. 104323, 2022, doi: https://www.sciencedirect.com/science/article/abs/pii/S2352710222003369

[3] A. Zaaoumi, A. Bah, M. Alaoui, A. Mechaqrane, and M. Berrehili, "Application of artificial neural networks and adaptive neuro-fuzzy inference system to estimate the energy generation of a solar power plant in Ain Beni-Mathar (Morocco)," in *2018 10th International Conference on Electronics, Computers and Artificial Intelligence (ECAI)*, 2018, pp. 1–6. doi: 10.1109/ECAI.2018.8679015.

[4] H. Tindra, I. D. Sara, and R. Adriman, "Daily Peak Load Forecast of Banda Aceh City Using Adaptive Neuro Fuzzy Inference System (ANFIS) Method," in *2023 2nd International Conference on Computer System, Information Technology, and Electrical Engineering (COSITE)*, 2023, pp. 238–243. doi: 10.1109/COSITE60233.2023.10249581.

[5] A. Azeem, I. Ismail, S. M. Jameel, and V. R. Harindran, "Electrical Load Forecasting Models for Different Generation Modalities: A Review," *IEEE Access*, vol. 9, pp. 142239–142263, 2021, doi: 10.1109/ACCESS.2021.3120731.

[6] D. Li, G. Sun, S. Miao, Y. Gu, Y. Zhang, and S. He, "A short-term electric load forecast method based on improved sequence-to-sequence GRU with adaptive temporal dependence," *Int. J. Electr. Power Energy Syst.*, vol. 137, p. 107627, 2022, doi: 10.1016/j.ijepes.2021.107627.

[7] Y. T. Nugraha and M. Irwanto, "Modelling Demand for Energy Sources as Alternative Energy in the Province of North Sumatra," *J. Renew. Energy, Electr. Comput. Eng.*, vol. 2, no. 2, p. 84, 2022, doi: 10.29103/jreece.v2i2.9278.

[8] I. M. El-Hasnony, S. I. Barakat, and R. R. Mostafa, "Optimized ANFIS Model Using Hybrid Metaheuristic Algorithms for Parkinson's Disease Prediction in IoT Environment," *IEEE Access*, vol. 8, pp. 119252–119270, 2020, doi:

10.1109/ACCESS.2020.3005614.

[9] P. Almaleck, S. Massucco, G. Mosaico, M. Saviozzi, P. Serra, and F. Silvestro, "Electrical consumption forecasting in sports venues: A proposed approach based on neural networks and ARIMAX Models," *Sustain. Cities Soc.*, vol. 100, p. 105019, 2024, doi: 10.1016/j.scs.2023.105019.

[10] J. Peng, S. Gao, and A. Ding, "Study of the short-term electric load forecast based on ANFIS," in *2017 32nd Youth Academic Annual Conference of Chinese Association of Automation (YAC)*, 2017, pp. 832–836. doi: 10.1109/YAC.2017.7967525.

[11] Y. Tri Nugraha, M. F. Zambak, and A. Hasibuan, "Perkiraan Konsumsi Energi Listrik Di Aceh Pada Tahun 2028 Menggunakan Metode Adaptive Neuro Fuzzy Inference System," *CESS (Journal Comput. Eng. Syst. Sci.*, vol. 5, no. 1, pp. 104–108, 2020, doi: 10.24114/cess.v5i1.15624.

[12] Y. T. Nugraha, K. Ghabriel, and I. F. Dharmawan, "Implementasi ANFIS Dalam Prakiraan Konsumsi Energi Listrik Di Kota Medan Pada Tahun 2030," *RELE (Rekayasa Elektr. Dan Energi) J. Tek. Elektro*, vol. 4, no. 1, pp. 55–59, 2021, doi: 10.30596/rele.v4i1.7826.

[13] A. Qazi *et al.*, "Towards Sustainable Energy: A Systematic Review of Renewable Energy Sources, Technologies, and Public Opinions," *IEEE Access*, vol. 7, pp. 63837–63851, 2019, doi: 10.1109/ACCESS.2019.2906402.

[14] A. A. Zakri, M. W. Mustafa, and I. Tribowo, "ANFIS Design Based on Prediction Models for The Photovoltaic System," in *2019 International Conference on Sustainable Information Engineering and Technology (SIET)*, 2019, pp. 234–239. doi: 10.1109/SIET48054.2019.8986133.

[15] T. İnan and A. F. BABA, "Prediction of Wind Speed Using Artificial Neural Networks and ANFIS Methods (Observation Buoy Example)," in *2020 Innovations in Intelligent Systems and Applications Conference (ASYU)*, 2020, pp. 1–5. doi: 10.1109/ASYU50717.2020.9259894.

[16] D. K. Ghose, K. Tanaya, A. Sahoo, and U. Kumar, "Performance Evaluation of hybrid ANFIS model for Flood Prediction," in *2022 8th International Conference on Advanced Computing and Communication Systems (ICACCS)*, 2022, vol. 1, pp. 772–777. doi: 10.1109/ICACCS54159.2022.9785002.