COMPARISON OF TECHNIQUES FOR LONG-TERM TRANSFORMER LOAD FORECASTING: A SYSTEMATIC LITERATURE REVIEW

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***Abstract*—Forecasting transformer loads in the electricity sector can help plan the development of power plants, transmission networks, and consumer distribution by predicting future actions that will be taken by energy providers. There are several ways to anticipate the proper and accurate use of artificial intelligence (AI) technology, including time series forecasting and machine learning or deep learning. Using journals from the last five years, we will conduct a systematic evaluation of the literature on load forecasting techniques to identify the most effective approaches for predicting long-term loads. The best method for predicting long-term burden is the linear regression method, based on the findings of a comprehensive literature review study that has been conducted. The best data for long-term load forecasting includes load data from the last two years as well as several other factors such as temperature and humidity.**

Keywords—deep learning, load forecasting, machine learning, systematic literature review, time series, transformer

I. INTRODUCTION

The demand for energy will rise quickly along with the nation's economic sector's development [1][2]. Transformers serve a vital role as the only device for transforming power by converting voltage from high voltage to high voltage. As one of the crucial parts of the electricity system, from electric power generation to transmission through transmission networks and substations to distribution to customers, transformers play a crucial role. low, or the opposite. Planning, buying, installing, operating, and maintaining the transformer will thus have an impact on the financial gains realized by the energy supplier as well as the standard of the electrical supply delivered to customers [3]. Therefore, two of the factors to consider while investing in transformers are increasing the power load and computing distribution losses [4].

Transformers are among the most expensive assets, and their purchase is made with great consideration and calculation for the long term. The employment of transformers, which convert power from generators to consumers with a range of voltages from 220V to 380V to high voltage at 150kV and extra high voltage at 500kV, is another crucial part of the electrical system [5]. According to SPLN 17-1979 standard standards [6], the transformer is loaded up to 80% of its full capacity [2][7][8]. With frequent maintenance and remedial action based on test findings, this seeks to prolong the lifespan of the transformer itself [9].

Electricity load forecasting can be done using Artificial Intelligence (AI) technology, either machine learning or deep learning, to estimate the actions that will be taken by electricity providers in the future. This will aid in the planning of future development in terms of electricity generation, transmission systems, and distribution to customers. Long-term load forecasting may be done in a number of ways, including by employing time series, trend predictions, and linear regression algorithms [2][10].

The findings of load forecasting have a significant error value, with MAPE results of 6%–9% [4][11], according to a number of earlier studies. Because predicting can be considered good if the error value achieved is near 0, the forecast is thus labeled as bad. Therefore, utilizing relevant publications from 2018 to 2023, this journal will examine the literature review relating to long-term load forecasting techniques. The approaches used in predicting long-term loads, including the method employed, the most efficient use of the historical data period for modeling, as well as the stages used in modeling so that forecasting can be done, will be compared in many selected journals. The appropriate modeling processes will then be determined based on the data and journals utilized, with findings established and judgments made on techniques, selection, and usage of historical data.

II. RELATED WORKS

Several research works may be cited in research on time series analysis and artificial intelligence (AI) for long-term load forecasting. Using time data and the fuzzy approach to anticipate loads is one example [12]. Based on this study, it is known that predicting is linear since linear data is used and linear outcomes are likewise achieved. Furthermore, it is well recognized that fuzzy forecasting produces more accurate outcomes than the time series approach. In addition, another study [13] presents a thorough analysis of numerous load forecasting models pertaining to various time periods and takes into account their use in diverse industries to assess methodologies and models in electrical load forecasting.

The employment of various methods has been thoroughly investigated in a number of studies that have previously been published, including the use of model-based transformers for short-term load forecasting [14] and the Fuzzy Time Series Cheng approach for medium-term forecasting [15]. For both short- and long-term forecasting, there are still a lot of strategies that may be researched [16]. Based on the idea that there are numerous methods that may be used for forecasting, this research was done to establish whether a strategy is preferable to use when forecasting long-term loads by utilizing AI or the time series method.

III. METHODOLOGY

The systematic literature review, or SLR, approach is used in this study. In order to obtain answers to a specific research issue, SLR is a methodical technique for locating, evaluating,

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and analyzing facts and evidence from prior research [17]. Table 1 below explains the study questions in more detail.

TABLE I. RESEARCH QUESTION

Num.	Question	Objective
RQ1	How do the SLR comparison results relate to the methods used in long-term load forecasting?	Analyze the comparison of long-term electricity load forecasting methods with the SLR method.
RQ2	What are the results of the analysis regarding what data is used to forecast long-term electricity loads?	Determine how to utilize quality data for long-term forecasting after analyzing the usage of data for long-term forecasting of electrical demands based on SLR results.
RQ3	What approach is most effective for predicting long-term electrical loads with the highest degree of accuracy?	Based on SLR findings, evaluating the best technique to achieve the maximum accuracy value in long-term power load forecasting

The SLR phases, which are shown in Figure 1 below, can be thought of as a research technique once the research questions have been established.

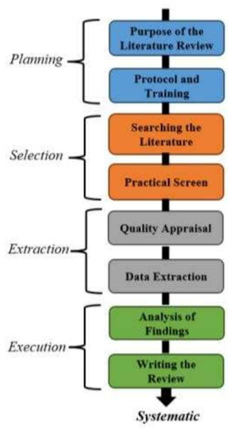

Fig. 1. A Systematic Guide To Doing SLR

Based on Figure 1, it is clear that the following procedures are taken in a methodical manner when utilizing the SLR technique as a foundation for research [18].

1) Purpose of the literature review: Determining the goals and anticipated outcomes of the study to be conducted is the first step in research utilizing SLR. Specifically, to give a system the highest accuracy in predicting long-term loads by applying AI and time series, the research questions are defined in this stage as aims and anticipated results.

2) Protocol and training: Harmonize perceptions, procedures, and standards in conducting SLR because this research is carried out by more than one person so that consistent research results are obtained.

3) Searching for the literature: Search for official literature that has been indexed nationally by SINTA or GARUDA and globally by organizations like IEEE, ScienceDirect, Google Scholar, and Elsevier after conducting a literature search using mutually agreed-upon techniques, processes, and standards, such as utilizing agreed-upon keywords.

4) Practical screen: This phase serves as an explanation of the restrictions that decide whether a piece of literature will be examined or not, such as limiting the literature selection to works that address long-term load forecasting utilizing AI and time series technology.

5) Quality appraisal: The literature that made it through the previous round is chosen at this step. In order to gain the literature needed to go on to the next step, Based on the literature's publishing year, 2019–2023, the choice was determined.

6) Data extraction: The identified literature will be systematically summarized using tables, and mapping will be done in regards to the background, study methodologies, research procedures, data sources, and research findings.

7) Synthesis of studies: The material that has been described will now be analyzed, including a comparison of the research methodologies employed, the research procedures, and the research findings from the literature that has been gathered.

8) Writing the review: The final step is writing, which is done in accordance with research writing guidelines and describes the SLR results as a summary of the study's findings.

IV. RESEARCH RESULT

Load forecasting in the energy industry, particularly in Indonesia, will be able to have a very big impact since the planning is divided into many designs, such as RUPTL. Based on the study objectives in Table 1, a literature search was done using predetermined keywords, aspects, database kinds, and research journals, and a total of 78 pieces of literature were discovered. Following the completion of the selection phase for quality rating, nine journals that may contain the solutions to research questions that need to be examined in further depth were received. The results of the SLR comparison with regard to the methods used to anticipate long-term loads are summarized in Table 2.

Various types of data are employed for predicting long-term electrical loads. Long-term forecasting is the practice of making predictions for a time frame between two and ten years. The past few years prior to the installation of the forecasting of electric demands might be utilized for the period of data collection employed for this purpose. Electricity loading information during a specific time period serves as the major source of data for load forecasting. The average loading data for a year is what is utilized. The business plan for electricity supply contains this set of facts. In addition to using electrical load data, temperature and humidity data may also be utilized to anticipate electrical loads. The pattern of utilizing air conditioning, which is a frequent habit for individuals when the weather is high, is affected by the usage of temperature and humidity variables owing to fluctuations in temperature and humidity. Of course, air conditioning use will affect how much power is used.

Load forecasting can be done using various forecasting methods, as shown in the journals above. Short-term load forecasting can be done using various methods, including Autoregressive Integrated Moving Average (ARIMA), Constructive Back Propagation Neural Network (CBPNN), Fuzzy Multi-Attribute Decision Making Decomposition Feed Forward Neural Network (FMADM-Dec-FFNN), Adaptive Neuro Fuzzy Inference System (ANFIS) [22], Feed Forward Backpropagation Neural Network (FFBNN) [23], Different

Generation Modalities (DGM) [24], Deep Learning Neural Network [25][26], and Deep Residual Network [27]. However, the most efficient forecasting of transformer loads at substations is carried out over a long period of time because this is related to the electricity provider's ability to meet consumer needs, which is also related to system reliability.

TABLE II. RELEVANT ARTICLE IN FIELD STUDY

No.	Journal Title	Data Used	Method	Results
1	Forecast electricity demand in commercial building with machine learning models to enable demand response programs, 2022 [28]	Loading 220336 data points during a 6-year period, from January 1, 2013, to December 31, 2018, at a rate of once every 15 minutes.	LSTM and SVM with evaluation metrics MAE, MAPE, and RMSE	The LSTM model was discovered to produce superior outcomes compared to the SVM model. The SVM model is appropriate for loading predictions with small-scale datasets, but the LSTM model is better at processing complicated data, but the data is unstable in training data.
2	Prediction of Electrical Load in Banjarbaru City Using Backpropagation Neural Networks, 2021 [11]	Data on the amount of electricity load in the city of Banjarbaru over a period of 9 years with 12 input units	Backpropagation Neural Network Method	The study's findings show that using four hidden layer simulations during the artificial neural network training stage, a 12-12-1 architecture with a MAPE value of 6.597% and RMSE of 0.032222 was achieved. The MAPE value for the testing stage was 7.918%, and the RMSE was 0.070479, making it possible to fairly anticipate the amount of electrical demand. The MAPE score was 12.366% and the RMSE was 0.113272, both of which indicate that the prediction results were poor since the quantity of power generated in December 2018 compared to January 2019 was significantly lower.
3	Long Term Forecasting of Electricity Loads in the Household Sector in East Java Using Trend Projection and Linear Regression Methods, 2020 [2]	PLN East Java RUPTL data 2020-2035 and population data from the East Java BPS website.	Trend projection and Linear Regression by comparing the two methods to get the best method.	The results of this study were obtained for the MAPE Trend Projection method of 1.33% in forecasting the number of subscribers and 1.49% in forecasting connected power, while for the MAPE Linear Regression method of 0.717% in forecasting the number of subscribers and 0.739% in forecasting connected power
4	Load Forecasting at the Mantingan Substation: Determining Transformer Capacity Using the Linear Regression Method, 2021 [29]	electricity data in the Mantingan GI area before 2019	Linear regression method	The aggregate anticipated increase in peak load for the three feeders, namely Sine, Trinil, and Walikukun, amounts to 18.8 MVA starting from 2019, with an average annual growth rate of 18.66%. The substation is capable of meeting the demand for the next eight years, thanks to its 60 MVA capacity. This determination is based on predicted load estimates, with a peak load of 33.21 MVA expected in 2026, which represents the highest peak load for the next eight years. The usage factor (UF) value of 72.29% for the 60 MVA transformer was determined by utilizing two transformers, one with a 30 MVA capacity and the other with a 60 MVA capacity. This aligns with the UF standard of below 80% for PLN substation equipment.
5	Estimation of Electrical Load Power at the Cengkareng Substation Using the Decomposition Model Time Series Method, 2019 [30]	PT. PLN (Persero)'s Cengkareng Substation Power Load Data Set, a time series from 2010 to 2017,	The CRISP-DM approach was then used to construct the time series method.	It was shown through calculations and analysis that the main substation experienced overload in every month of 2022. With the aid of the electric load power estimate application, PT. PLN (Persero) may evaluate the substation electric load power data using the time series decomposition model. The results of the tests used to confirm forecasting errors were MAD = 9.11, MSE = 137.16, and MAPE = 9.11%.
6	Optimization of Forecasting of Jember Substation Loading Using Comparison of Time Series and Fuzzy Methods as a Basis for Transformer Uprating, 2020 [12]	Population growth, improvements to the educational system, the health care system, and the Jember Substation's load history during a six-year period from 2013 to 2018	Time series and fuzzy models	The fuzzy method's forecasting error value is reduced when compared to time series. The time series method error values for transformers I, II, III, and IV are 4.5%, 3.9%, 3.87%, and 2.85%, respectively. The fuzzy method error values for these same transformers are 2.03%, 1.97%, 2.68%, 3.3%, and 1.83%, respectively. As a consequence, when estimating loads at the Jember Substation, the fuzzy methodology is more accurate than the time series method.
7	Electrical Load Prediction Using a Backpropagation Type Artificial Neural Network Algorithm, 2020 [31]	Data on population growth, gross regional domestic product, and transformer loading at the Bumiayu Main Substation for the previous ten years.	Algorithm of an artificial neural network with back propagation type	The prediction results that have been made for the 2018–2027 period show a trend of increasing peak loads every year. In 2027, the peak load of power transformer 2 is estimated at 23.17 MW, or equivalent to 77.23% of the capacity of power transformer 2, and can be categorized as an optimal standard transformer load.
8	Forecasting Long Term Electrical Energy Needs in Bali Province for the Year 2020 –	Population, Gross regional domestic product, gross regional domestic product per	Neural networks have the advantage of being able to learn based on historical	According to the simulation's predictions, Bali Province will need 5,772 GWh of electrical energy in 2020; this amount will rise to 6,523 GWh in 2025 and to 8,551 GWh in 2030. The MAPE for the 2019

	2030 Using Neural Networks, 2021 [32]	capita, consumer price index	data patterns used in training.	RUKN as a result of this prediction is 3.29%, which is still less than the PLN's provisions of 10%.
9	Long-term forecasting for growth of electricity load based on customer sectors, 2022 [33]	Monthly electricity consumer data from January 2018 to December 2020	Linear regression	The predicting value, such as in the home sector (0.142%), business sector (0.085%), industry (1.983%), and total number of consumers (0.131%), has a low MAPE value as a result.

According to Table 1, it is evident that long-term load forecasting can be conducted through various approaches, including linear regression [2] [29] [33], as well as time series and fuzzy methods [12]. After a thorough examination of the findings, it can be concluded that the most effective method for long-term load forecasting is linear regression [33]. After comparing the outcomes of the reviewed methodologies, it was established that three methods can be employed for long-term electricity load forecasting: linear regression, time series, and fuzzy methods, as well as the utilization of backpropagation neural networks through the Matlab program. Subsequently, an analysis was conducted to determine the most suitable method for long-term electricity load forecasting, taking into consideration the forecasting error values associated with each method.

Based on the analysis results, it was observed that the linear regression method yielded the lowest mean absolute percentage error (MAPE) value at 0.085%, which is notably smaller than the MAPE values obtained from other methods. Specifically, the JST backpropagation method yielded a MAPE value of 6.59%, the time series method recorded a MAPE of 9.11%, and the combined time series and fuzzy model produced a MAPE of 1.97%. Furthermore, the neural network method resulted in a MAPE of 3.29%, the trend projection method showed a MAPE of 0.717%, and the linear regression method demonstrated a similar MAPE of 0.717%.

V. Conclusion

Based on the findings derived from the comprehensive literature review, it becomes evident that the dataset used in long-term forecasting primarily consists of electricity consumption data over the past three years, collected on a monthly basis. In the context of long-term electrical load prediction, several data types are relevant, including electricity usage data, temperature records, and humidity data. The forecasting techniques employed for long-term projections encompass the linear regression method, the time series approach, and the fuzzy method, with the backpropagation neural network method implemented through the Matlab program. Upon analyzing the obtained results, it can be deduced that the most effective method for long-term electrical load forecasting is linear regression. This conclusion is supported by Mean Absolute Percentage Error (MAPE) values of 0.142% for the household sector, 0.085% for the commercial sector, 1.983% for the industrial sector, and 0.112% for the business sector.

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