The Number of Nodes Effect to Predict the Electrical Consumption in Seven Distinct Countries

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***Abstract*— This paper presents a machine learning-based approach for forecasting electrical consumption in seven selected countries across different geographical categories. The data, sourced from The International Energy Agency, is analyzed, and condensed to focus on specific nations: Northern (Norway, Canada), Southern (Chile, Australia), Four-season (France, Japan), and a Tropical country (Colombia). The unique electrical consumption patterns influenced by regional climate characteristics make this study compelling for machine learning applications, from the dataset comprising over 132,000 records from January 2010 to May 2023 across fifty-three countries, a refined dataset focusing on 791 data points from seven specifically chosen countries to simplify the study. Much of the paper details the machine learning design for forecasting electrical consumption. Specifically, Neural Network (NN) architecture is proposed to predict consumption. The input features encompass the year, month, and country, with the output being the predicted electrical usage.**

***Keywords*— Artificial neural network, forecast, hidden layers, load consumption**

I. INTRODUCTION

A. Background

Electricity consumption forecasting is crucial in energy management and policy formulation, mainly as it enables better resource allocation and infrastructure planning [1]. Optimizing energy usage and resource planning has become increasingly crucial with a growing global focus on sustainability. Electricity consumption is a vital indicator of a nation's energy usage and economic activity [2]. The need for accurate forecasting stems from several crucial factors. Some of them are discussed in this paper as well. Forecasting consumption aids in effectively planning and managing energy resources. It enables utility companies and governing bodies to anticipate demand fluctuations and adjust their production and distribution accordingly [3].

Predicting electrical consumption aids in the development of infrastructure and energy networks. By understanding future demands, governments and energy providers can make informed decisions about building new power plants, upgrading transmission lines, and improving energy storage systems. Fluctuations in energy consumption affect economic stability [4]. Accurate forecasting helps stabilize energy costs and prevents shortages, ensuring continuous and reliable energy supply for industries, businesses, and households. Efficient energy use is integral to environmental conservation. Also, this allows for better management of renewable energy sources, reduces waste, and aids in the transition to cleaner, more sustainable energy practices. Understanding the nuanced consumption patterns within different regions is essential for accurate predictions [5]. The studies also focus on a machine learning approach to forecast electrical consumption in seven countries with diverse geographical characteristics.

The selection of these countries based on geographical categories—Northern, Southern, Four-season, and Tropical—aims to capture the unique seasonal influences on electricity usage. For instance, Northern countries experience peak consumption in winter due to heating needs, while Southern nations peak in their respective summer months, often due to increased air conditioning demand. Tropical countries present a distinctive pattern characterized by consistent and stable annual consumption [6]. The details on the data reduction process from a vast dataset focus solely on the selected countries and the proposed usage of seven years' worth of data (2014-2021) for training the machine learning model, reserving the remaining data for testing purposes. Central to this research is developing an NN model for consumption forecasting. The chosen input features and the forecasted output play from the existing studies [6] intend to offer insights into the architecture and method employed in this machine-learning project.

This paper delves into the realm of electrical consumption forecasting, explicitly focusing on seven countries selected from different geographical categories: Northern (Norway, Canada), Southern (Chile, Australia), Four-season (France, Japan), and a Tropical country (Colombia). These countries were selected based on their distinct geographical characteristics, significantly affecting their electrical consumption patterns. The study of electrical consumption patterns in various geographic regions is essential as different climates and societal behaviors significantly influence energy usage [7]. Understanding these patterns through forecasting can contribute to more efficient and sustainable energy management strategies, benefiting both the economy and the environment.

B. Literature Review

In the dynamic landscape of energy management and policy formulation, electricity consumption forecasting is critical for resource optimization and strategic infrastructure planning. As already discussed, electricity consumption, as a fundamental indicator of a nation's energy usage and economic activity, plays a pivotal role in shaping policies and fostering sustainable practices. Accurate forecasting is not merely a statistical exercise but a strategic tool for utility companies and governing bodies to navigate the dynamic landscape of demand fluctuations, enabling them to anticipate, plan, and manage resources effectively. This literature review will explore the challenges and opportunities inherent in electricity consumption forecasting, shedding light on its multifaceted implications for energy resource planning, economic stability, and environmental conservation.

As a result of a research effort by Memorial University of Newfoundland, simulations are performed using MATLAB to forecast the electric load [8]. The hourly load consumption dataset from January 1, 2016, to March 31, 2020, is used in this research. It is found that the family of GPR models shows the best load forecasting performance because load forecasting is crucial for power systems planning, operation, and control. This paper focuses on developing a day-ahead load forecasting approach for the energy management system of a sustainable campus project. The study evaluates 19 regression model-based forecasting algorithms, with Gaussian Process Regression (GPR) models showing the best performance. Specifically, Rational Quadratic GPR and Exponential GPR are recommended as the best models for load forecasting. The proposed method in another research model [13] outperforms state-of-the-art forecasting methods and effectively captures the relatedness to provide between-community knowledge transfer in a real-world case study of two residential communities in Tallahassee, Florida.

A study on community building energy load forecasting reveals critical insights into the imperative need for enhancing building energy consumption efficiency, given its substantial impact on global energy usage [9]. It also underscores the significance of energy load forecasting as a pivotal strategy for optimizing energy utilization in building energy management. Incorporating Federated Learning (FL) in addressing privacy concerns arising from regulations such as GDPR is a noteworthy contribution. The study highlights FL's role in facilitating distributed feature learning while ensuring data privacy and security by training a shared machine learning model without direct access to the data on remote user devices. The call for further exploration into the practical application reliability of federated learning for building energy load forecasting is identified as a critical research area. The author successfully designed an intelligent building energy data platform, emphasizing its validation using a dataset from 10 UBC campus buildings [9]. This dataset is derived from electricity consumption data recorded through the SkySpark platform, providing a practical foundation for assessing the platform's performance.

A similar study to deal with electric load forecasting with the NN-based model, discusses the significance of electric load forecasting, particularly short-term forecasting, in optimizing power system operations and assisting participants in the electricity market [10, 15]. It emphasizes the importance of accurate load forecasting for developing power generation plans and improving the stability and economic efficiency of the power system. The study impressively highlighted the limitations of existing load forecasting models, particularly regarding interpretability. It mentions that while forecasting accuracy has improved with the development of machine learning techniques, the interpretability of the results has yet to be effectively improved. The study not only discussed the concept of using similar days in historical data for load forecasting, which is considered an essential method in practice but also proposes a new method called Neural-based Similar Days Auto Regression (NSDAR) that combines an NN model for similar day screening and an interpretable model for load forecasting based on similar days. The author could explain that power load exhibits strong periodicity and similarity to human social activities, and incorporating similar day load data can significantly improve prediction accuracy. It also aims to address the reduced interpretability caused by black-box models and enhance the utilization of similar day-based methods.

As mentioned before, Power load forecasting is crucial for ensuring the stability and reliability of electricity supply and demand in the power market, especially in the context of modernization and rapid economic development. Hence, Traditional load forecasting methods, such as time series analysis and regression prediction, are no longer suitable for today's nonlinear and complex power systems. Some studies claim that the Data-driven artificial intelligence methods, including deep learning techniques like CNN, Long Short-Term Memory (LSTM), and Bidirectional Long Short-Term Memory (BiLSTM), have shown better prediction accuracy in power load forecasting due to their ability to extract complex abstract features [11]. The author points out that traditional prediction methods face challenges in accurately predicting power load sequences with nonlinear and non-stationary characteristics. The single machine learning models may suffer from local optimization or overfitting issues. As per the author, the GWO-VMD-GTO-CNN-BiLSTMS model combines deep learning with statistics to address the complexity and uncertainty of load forecasting, aiming for improved stability and accuracy.

Load forecasting is essential for energy management and control of buildings in residential neighbourhoods. The uncertain nature of electricity demand in these areas requires a unified approach to overall load prediction. Therefore, a time-series clustering scheme based on the k-medoids clustering algorithm and Dynamic Time Warping (DTW) algorithm to classify power profiles has been used for the experiment [12]. The Additive Gaussian Process (AGP) is used for effective load forecasting at each cluster level. The paper evaluates the proposed clustering and prediction strategies using load data from seventeen real-life houses in the Quebec, Canada region, explicitly focusing on winter days and electric heaters. The paper highlights the limitations of traditional clustering techniques in load forecasting, which often use Euclidean distance and lack one-to-many or many-to-one distancing. It also emphasizes the need to validate forecasting techniques on real-life consumption data. The proposed load forecasting method, including k-method clustering and consensus clustering, is applied to synthetic and actual energy consumption datasets in a group of houses. The consensus-based approach improves the scalability and accuracy of the forecast by identifying critical targets with high similarity of consumption levels.

This review emphasizes the ripple effects of accurate forecasting, extending beyond economic stability to influence infrastructure development, energy network enhancement, and the delicate balance needed for a sustainable future. It explores how fluctuations in energy consumption impact economic stability, and how precise predictions become crucial for stabilizing energy costs, preventing shortages, and ensuring a continuous and reliable energy supply for industries, businesses, and households. Moreover, it demonstrates the significance of adopting a machine learning approach to forecast electrical consumption, which takes centre stage and is promising to unveil the architecture and methodology underpinning this innovative project. Through this exploration, the review aims to contribute to the field of energy forecasting and the broader discourse on efficient and sustainable energy management strategies, bridging the areas of economy and environment.

The significant gap in these studies is the usage of short-term load forecasting. Short-term load forecasting, crucial for real-time decisions, faces limitations, including sensitivity to external factors, a brief planning horizon, reliance on real-time data, complex modelling challenges, and difficulty anticipating long-term trends and dynamic loads. The volatility in demand and the need for rapid operational adjustments underscore the constraints of relying solely on short-term forecasts for comprehensive energy planning. Another limitation of these studies is that these systems only deal with specific regions or climatic conditions. These systems need more adaptability to diverse environments. Their struggle to predict loads accurately outside predefined parameters and limited applicability hinder comprehensive insights for areas with varying climatic profiles or rapidly changing energy demands. This lack of versatility makes these systems less dependable in handling broader and evolving energy landscapes.

II. METHOD

A. Datasets

This work aims to build and train an artificial intelligence (AI) model to predict and forecast energy consumption based on secondary research data gathered by the International Energy Agency (IEA), and it is publicly available for researchers [14]. The original data set has over 130K elements representing electrical energy production and consumption in more than fifty countries worldwide. In this research, data from seven countries were selected over ten years (2014 – 2023) across 12 months based on energy consumption and production patterns among four categories: northern countries (Norway and Canada), southern countries (Chile and Australia), four-season countries (France and Japan), and a tropical country (Colombia).

Figure 1 illustrates the unique pattern of electrical consumption of four distinct categories in 2020. For instance, while Canada and Japan had peak electrical consumption in winter (December), Japan also had another consumption peak in summer (August). The increase in energy consumption in both countries during winter was due to the need for heating loads while increasing the consumption during summer in Japan was due to cooling loads (e.g., air conditioners), which were not needed in Canada. On the other hand, a tropical country such as Colombia had a unique flat pattern of electrical consumption throughout the year. This uniqueness makes designing projects of machine learning more interesting.

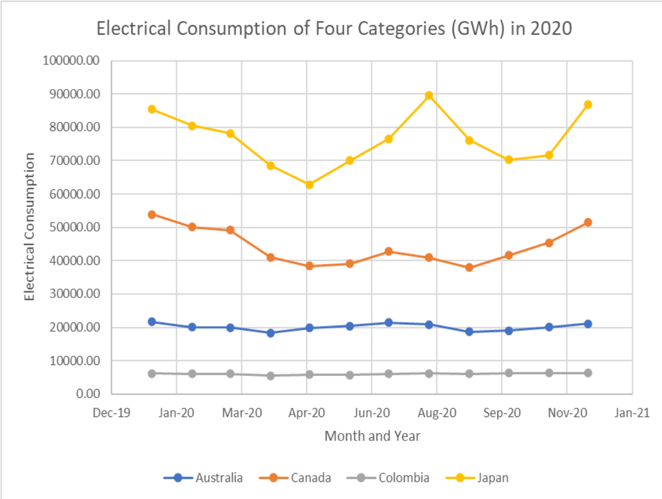

Figure 1. The electrical consumption pattern of selected countries

B. Data Preprocessing

To enhance the accuracy of the proposed model, a data cleaning process was applied to ensure that utilized data represent actual energy consumption. The data cleaning process includes identifying and correcting inaccuracies and inconsistencies in the dataset, which were minimal. Moreover, the data normalization process is essential to avoid biasing in model training, especially in contexts where there are large magnitude variations between energy consumption among countries in the scope of this study. The maximum recorded energy consumption was 96494.5 GWh while the minimum was only 4884.9 GWh. Linear normalization of data was applied according to Eq.1.1 and the values of normalized energy consumption ∈ [0,1].

$$P_{normalized} = \frac{P_{actual} - P_{min}}{P_{Max} - P_{min}} \qquad (eq. 1.1)$$

As this modelling is for a linear regression scenario, all input parameters are to be placed in a normalized continuous dimension (scale) and this was applied to months, years, and countries.

C. *Neural Network Model*

In this research, an artificial neural network (ANN) was selected to model and predict the electrical energy consumption in countries under the scope of this study. The proposed ANN consists of an input layer with three inputs being (month, year, and country), a single hidden layer with N nodes, and an output layer with a single that represents the predicted power consumption. The structure of the proposed ANN consists of a fully interconnected network as shown in Figure 2 where each link has an updatable weight and each neuron in the hidden or output layers has a biasing term. MATLAB has been used to build, train, and validate the proposed ANN as well as to predict the outputs utilizing the Neural Fitting Toolbox. The proposed ANN uses two types of activation functions (h); Hyperbolic tangent sigmoid transfer function (h_1) at all neurons of hidden layer, and Linear transfer function (h_2) at the output neuron as shown in Figures (a) and 3 (b), respectively. The utilized activation functions are given in Eq.2.1 and Eq.2.2:

$$h_1(n) = tanh\ tanh\ (n) = \frac{2}{1+e^{-2n}} - 1 \quad \rightarrow Eq.2.1$$

$$h_2(n) = n \quad \rightarrow \ Eq.2.2$$

The output of hidden layer neurons and final output were calculated as shown in matrix form in Equ.3.1 and Equ.4.1, respectively. Equ.3.2 and Equ.4.2 represent in compact form neuron output and final output relations, respectively.

$$\begin{bmatrix} q_1 \\ q_2 \\ \vdots \\ q_N \end{bmatrix} = h_1\left(\begin{bmatrix} W_{11} & W_{12} & W_{13} \\ W_{21} & W_{22} & W_{23} \\ \vdots & \vdots & \vdots \\ W_{N1} & W_{N2} & W_{N3} \end{bmatrix}\begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} + \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_N \end{bmatrix}\right) \quad (Eq.3.1)$$

$$\mathbf{q} = h_1(\mathbf{Wx} + \mathbf{b}) \qquad (Eq.3.2)$$

$$y = h\left(\begin{bmatrix} W_1 & W_2 & \cdots & W_N \end{bmatrix}\begin{bmatrix} q_1 \\ q_2 \\ \vdots \\ q_N \end{bmatrix} + [b_y]\right) \quad (Eq.4.1)$$

$$\mathbf{y} = h_2\left(\mathbf{W^{(2)}q} + \mathbf{b_y}\right) \qquad (Eq.4.2)$$

D. *Training and validation subsets*

The dataset was divided into two subsets i.e., training set and testing set. Energy consumption data for eight years (2014 – 2021) were used for training the proposed CNN model and the remaining two years of data (2022 – 2023) were used for validation and evaluating the performance of the proposed model. This splitting reflects that 85% of the available dataset is used for training and 15% is used for validation and testing. Afterwards, the trained model was used to predict electrical energy consumption in the selected country in the year 2024.

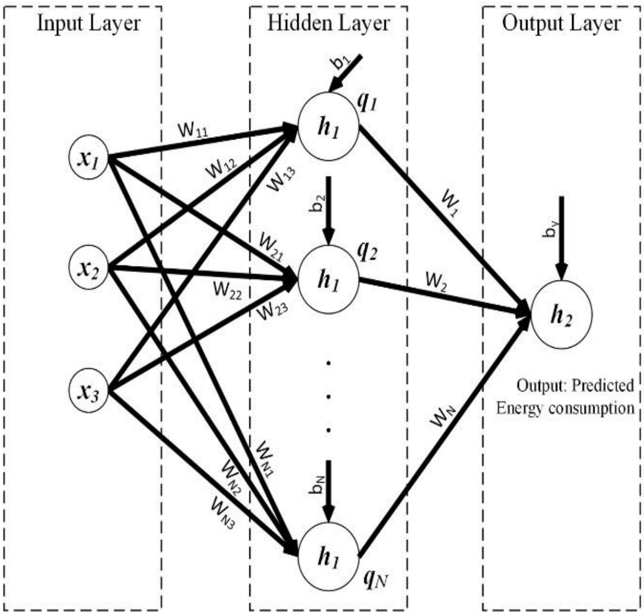

Figure 2. Structure of proposed CNN

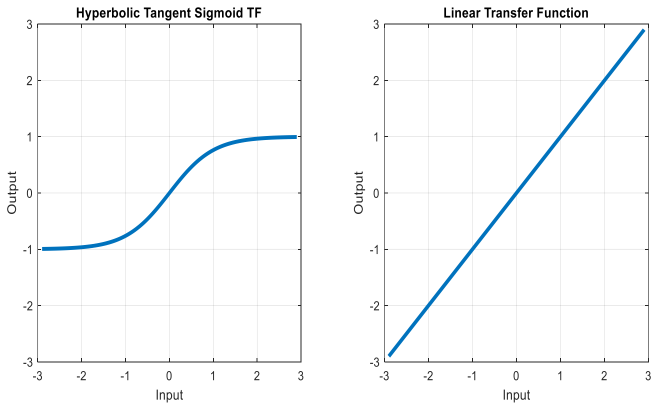

Figure 3. Types of Activation Functions used in the ANN.

E. *Number of Neurons*

In this research, we study the effect of the number of neurons (N) in the hidden layer on the performance of the proposed ANN in predicting energy consumption in countries under the scope of this research. Initially, we started by training the ANN model with N=5 and measuring its performance and predictions. The number of neurons in hidden layers increases from N=10 to N=40 in steps of 5 in each study i.e., N={5,10,15,20,25,30,35,40}. The study illustrates the effect of CNN design complexity on its performance in terms of biasing and variance. Bias is the limitation of the model to represent the true relation between input and output for a given data set and it can reflect the underfitting of the model to data. The variance, however, is the variety of model performance depending on data sets. High variance is that the model could have exceptionally low training error but when exposed to test data it has high testing error. This research will show the optimum number of N, which results in the desired performance ANN model with low biasing and low variance.

F. Model Flowchart

The process of model training starts with random first weights and biases that are applied to input data to obtain the predicted output in the first iteration. The error is calculated by comparing the predicted output with the desired output and the error is used to update the weights and biases of the model using the Levenberg-Marquardt backpropagation (LMBP) algorithm. LMBP is a hybrid error backpropagation (BP) technique that minimizes the sum of square errors by combining Gradient Descent and Gauss-Newton optimization methods. It has a rapid convergence and high precision compared to standard BP algorithms. After training, the model is used to predict power consumption in a selected country at a selected time. Figure 4 illustrates the flowchart of the proposed CNN model.

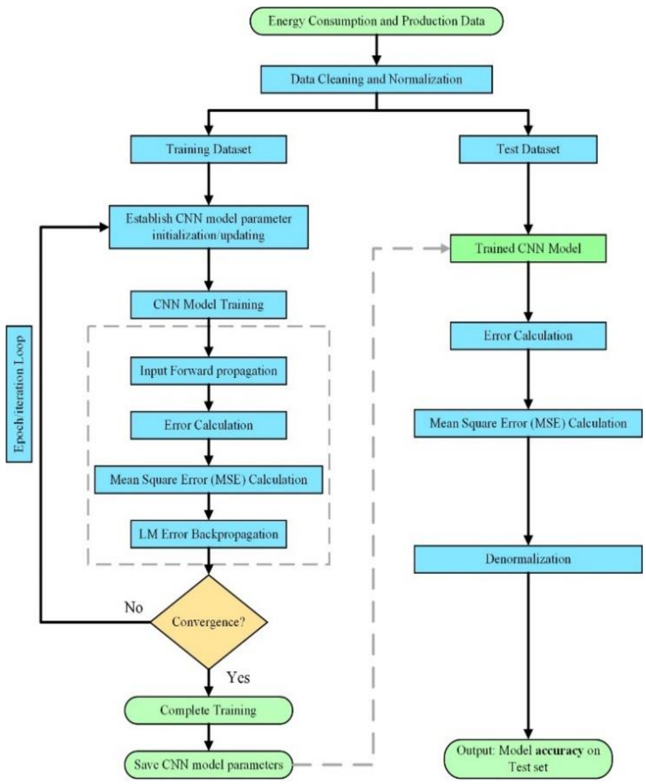

Figure 4. Flowchart of proposed ANN model

III. RESULTS AND DISCUSSION

The ANN generates forecasted outputs measured in GWh, with predictions contingent upon the number of nodes ranging from 5 to 40. The study specifically focuses on the ANN's performance, examining the input electric consumption versus the output estimated consumption for each country on a yearly and monthly basis. The forthcoming sections supply a detailed discussion of the ANN's proficiency in handling diverse datasets and layer configurations.

A. Results in Training

This section presents outcomes derived from training the AAN using data from 2014 to 2021. The results highlight the AAN's effectiveness in processing the original input dataset and generating consumption estimates across layers ranging from 5 to 40 nodes. Figures 5 and 6 illustrate the Training Results for the original data and all layers, specifically for the year 2021, simultaneously highlighting Australia and Norway. The analysis offers comprehensive insights into the AAN's performance, emphasizing its ability to predict electric consumption across different layers and for various countries.

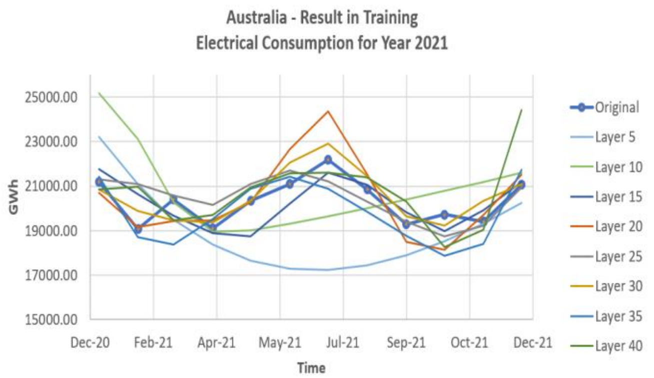

Figure 5. Result in Training for Australia | Original and Layer 5-40 for Year 2021

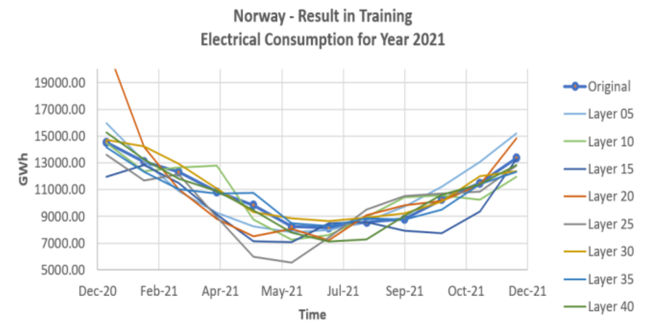

Figure 6. Result in Training for Norway | Original and Layer 5-40 for Year 2021

B. Result in Testing

This segment presents the expected outcomes, namely the power consumption estimates for the countries in the year 2022. Figures 7 and 8 provide a comprehensive visual representation of the original input data alongside the month-wise estimated results across all layers of the AAN for both Australia and Norway simultaneously.

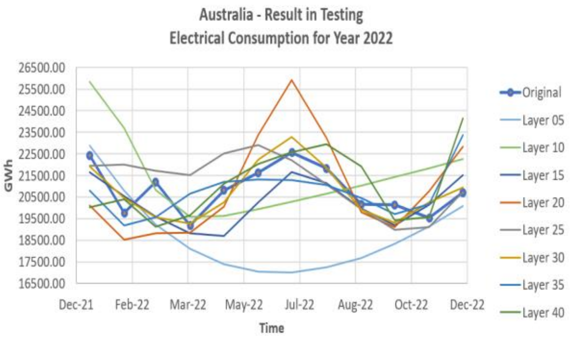

Figure 7. Result in Testing for Australia | Original and Layer 5-40 for Year 2022

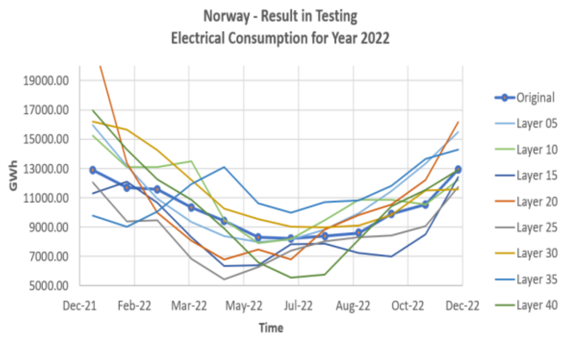

Figure 8. Result in Testing for Norway | Original and Layer 5-40 for Year 2022

Comparing the Results in Training for the year 2021 with the Results in Testing for 2022 reveals that Layer 30 produces outputs closest to the original data. Despite the contrasting weather cycles of the two sample countries, affecting their electrical consumption patterns, Layer 30 within the AAN demonstrates proximity to the ideal estimated results. This observation serves as a sign that the AAN, specifically with Layer 30, yields optimal projections. Furthermore, an added matrix, the Root Mean Square Error (RMSE), is employed to assess the AAN's performance.

C. Evaluation of Model Accuracy through RMSE

The Root Mean Square Error (RMSE) serves as a widely adopted metric in machine learning to assess the precision of a regression model. It quantifies the average magnitude of errors between predicted values and actual values, defined in Eq.5.1 as follows:

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

Where:

- n is the number of data points.
- y_i is the actual value of the target variable for the i^{th} data point.
- $\hat{y}_i$ is the predicted value of the target variable for the i^{th} data point.

RMSE computation involves squaring the differences between predicted and actual values, averaging these squared differences, and later taking the square root to yield the root mean square error. Figure 9 provides a visual representation of RMSE for the Training Results, Testing Results, and all layers.

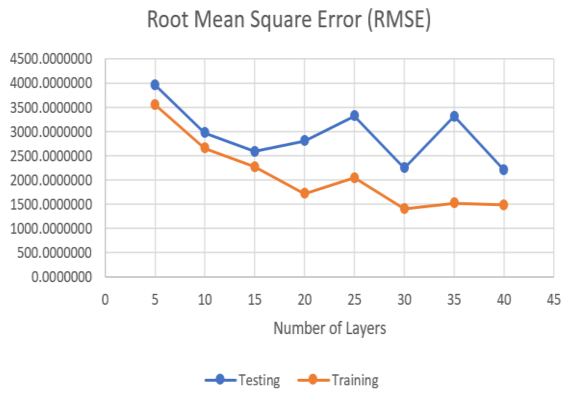

Figure 9: RMSE for The Testing and Training | Layer 5-40

In general, lower RMSE values correspond to enhanced model performance, with an RMSE of 0 indicating perfect prediction. As depicted in Figure 9, a cross-comparison of RMSE values across all layers for both Testing and Training is presented. Notably, among models with varying layers, the Layer 30 model exhibits significantly lower RMSE and is consequently selected for subsequent predictions.

D. The Predictions

Utilizing the AAN model with the lowest RMSE, the predicted electrical consumptions for the Year 2024 are presented in Figure 10. Based on the prediction chart presented in Figure 10, it can be deduced that the predicted power consumption in Northern countries: Canada and Norway, exhibits an escalating consumption trend with peaks at the beginning and end of the year. This observed pattern may be attributed to the heightened heating load during the extreme winter conditions prevalent in these months. Notably, a decrease in consumption is indicated around June, implying a milder summer in the region.

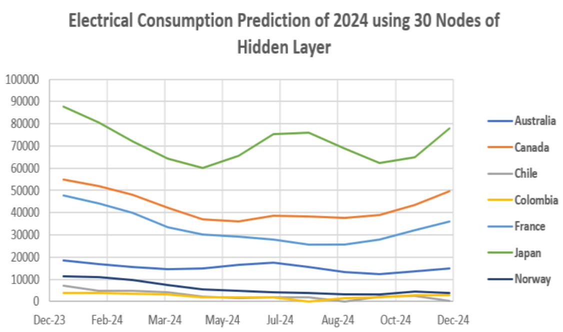

Figure 10. 2024 Predicated Electrical Consumption| Layer 30

IV. CONCLUSION

The conclusion, this research developed a machine learning-based approach for forecasting electrical consumption in seven selected countries across different geographical categories. The utilized data was sourced from The International Energy Agency for selected countries including northern countries (Norway, Canada), southern countries (Chile, Australia), four-season countries (France, Japan), and a tropical country (Colombia) due to unique electrical consumption patterns influenced by regional climate characteristics. The analyzed results show that ANN with 30 nodes in the hidden layer achieved the lowest testing error (RMSE). The NN succeeded in predicting the future trends in 2024 despite the diversity of electrical consumption trends between them.

For future improvements, further tuning and optimization are needed for the current model before deployment to minimize the RMSE. Also, we use multi-layer ANN or CNN models to forecast the energy consumption along with including a larger number of neurons in the hidden layer of the ML model. Also, we can include a larger number of neurons in the hidden layer of the ML model. In addition, include further data points for enhancement of ML model training.

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