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Investigating the influence of switching from load forecasting to net load forecasting on the forecasting accuracy

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دراســـة تأثيــر التحول من التّنبــؤ بالحمل الكهربائــي إلى التّنبــؤ بصافي الحمل الكهربائــي على دقــة التّنبــؤ

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Abstract

Forecasting the electric load is important in the energy sector for ensuring a stable and economic power system operation. However, the increasing integration of non-dispatchable renewable energy sources, such as wind and solar power, into the grid has created a need for predicting the net load, that is, the amount of load remaining after renewable energy sources cover a portion of the total energy demand. The scientific literature contains numerous forecasting techniques and methods that can be used to forecast the load or the net load. Electricity companies may rely on a particular load forecasting method and apply it to net load forecasting as well. Therefore, this paper investigates whether this approach yields similar forecasting accuracy.

The research utilizes Adaptive Neuro Fussy Inference Systems (ANFIS) as an advanced artificial intelligence-based forecasting technique to predict the load and the net load using real historical data from the Spanish electricity grid which is characterized by a significant contribution of wind and solar power. The study also uses the root mean square error (RMSE) and mean absolute error (MAE) as evaluation criteria. The results show that, when using the same forecasting method, the accuracy of net load forecasting is lower than that of load forecasting. Therefore, when planning to integrate additional wind and solar power into the electricity grid, electricity companies should not rely on the same method for forecasting the net load but should take the necessary measures to restore the accuracy of net load forecasting to the desired level.

Keywords: Load forecasting, net load forecasting, forecasting methods and accuracy, ANFIS, wind and solar power .

الملخص

يُعدّ التّنبؤ بالحمل الكهربائي أمرًا بالغ الأهمّية في قطاع الطّاقة لضمان تشغيل مستقر واقتصادي للشّبكة الكهربيّة. ومع ذلك، أدى تزايد ضخ الطاقة المتجددة غير القابلة للتّوزيع، كطاقة الرّياح والطّاقة الشّمسية في الشّبكة الكهربيّة إلى ظهور الحاجة للتّنبّؤ بصافي الحمل، أي مقدار الحمل المتبقّي بعد أن تُغطّي مصادر الطّاقة المتجدّدة جزءًا من إجمالي الطّلب على الطّاقة. وتحتوي المؤلّفات العلميّة على العديد من تقنيات وطُرق التّنبّؤ التي يمكن استخدامها في التّنبّؤ بالحمل أو صافي الحِمل. قد يحدث أن تثق شركات الكهرباء بطريقة معينة للتّنبّؤ بالأحمال فتستخدمها في التّنبّؤ بصافي الحمل. لذلك، تدرس هذه الورقة ما إن كان ذلك يؤدي إلى الحصول على دقّة تنبّؤ مماثلة .

يستخدم البحث أنظمة الاستدلال العصبي الضّبابي التكيّفي (ANFIS) كتقنية تنبّؤ متقدّمة قائمة على الذّكاء الاصطناعي للتّنبّؤ بالحمل وصافي الحِمل بالاستفادة من بيانات تاريخيّة حقيقيّة تخصّ شبكة كهرباء إسبانيا، والتي تتميّز بمساهمة كبيرة من طاقة الرّياح والطّاقة الشّمسيّة. وتستخدم الدراسة أيضًا مقياسي جذر متوسّط مربّع الخطأ (RMSE) ومتوسّط الخطأ المطلق (MAE) كمعايير للتقييم، أظهرت النتائج أنه في حالة استخدام نفس طريقة التّنبّؤ فإنّ دقّة التّنبّؤ بصافي الحمل تقلّ عن دقّة التّنبّؤ بالحمل. وعلّيه، فإنّه عند التخطيط لدمج كميات إضافيّة من طاقة الرّياح والطّاقة الشمسية في الشّبكة الكهربيّة،

لا ينبغي لشركات الكهرباء الاعتماد على نفس الطريقة للتّنبؤ بصافي الحمل، بل يجب اتّخاذ التّدابير اللازمة لإعادة دقّة التّنبؤ بصافي الحمل إلى المستوى المطلوب.

الكلمات المفتاحية: التّنبؤ بالحمل الكهربائي، صافي التّنبؤ بالحمل الكهربائي، أساليب التّنبؤ ودقتها ، أنظمة الاستدلال العصبي الضّبابي التكيّفي، طاقة الرياح والطاقة الشمسية.

1.Introduction

Before the renewable energy era, there was a critical need for energy demand forecasting to ensure a continuous balance between consumer consumption and electricity generated from thermal and hydroelectric power plants. This balancing process is essential for maintaining the stability and reliability of the energy system. Furthermore, electricity companies need the most accurate forecasts possible for energy demand. By avoiding forecasting errors, significant financial and structural losses can be prevented, and significant savings can be achieved (Mamun, Al. 2020).

Over the years, the world has witnessed tremendous efforts to save the planet from the effects of environmental pollution and climate change. Among these efforts, electricity generation from renewable energy sources such as wind, solar, geothermal, biomass, ocean waves and tidal power, has begun to replace electricity generated from traditional power plants that rely on burning fossil fuels like coal, natural gas, and diesel. Besides being environmentally friendly, renewable energy has proven its economic viability, which has contributed to accelerating its growth and deployment, particularly wind and solar power, worldwide.

Both the International Energy Agency (IEA 2024) and the International Renewable Energy Agency (IRENA 2024) have confirmed increasing levels of global renewable energy penetration year after year. For example, the year 2024 marked the highest annual increase in renewable energy generation capacity compared to previous years. By the end of 2024, global renewable energy capacity reached 4448 GW representing an increase of 585 GW (+15.1%) over the previous year. Solar power contributed 1,865 GW (42%), representing an increase of 452 GW (+32.2%), while wind power contributed to 1,133 GW (25%), representing an increase of 113 GW (+11.1%). Hydropower, another clean energy source, also contributed a significant 1,283 GW in 2024 (29% of the total 4,448 GW). However, this represents an increase of only 15.0 GW (+1.2%) compared to 2023. Finally, other renewable energy resources; namely, bioenergy, geothermal energy and marine energy accounted for the remaining 0.4% of the total. It is clear from the above that solar and wind energy have become major sources of renewable energy.

Hybrid energy systems can contain two types of renewable energy sources: dispatchable such as biomass and hydropower and non-dispatchable such as solar and wind power. Non-dispatchable sources are those which cannot be relied upon to meet the demand as per request because the energy generated from them is volatile and uncontrollable by its nature (Siriwardana, K. M. M. H. 2022). Therefore, available energy from non-dispatchable sources (solar and wind power) should be injected directly into the grid to meet as much of the load demand as possible, while dispatchable sources (renewable and/or conventional) meet the remaining load demand. Again, to ensure the stability and reliability of the energy system, this remaining demand must be met by power generated from conventional generating units. In the literature, the difference between actual load and production from non-dispatchable renewable energy sources is defined as “net load” (Can, Ş. Ş. E. 2018). In other words, net load is the demand that must be met from dispatchable sources such as thermal and hydro power (Wang, Yi. 2017). Thus, net load differs from conventional load in that it refers to the contribution of renewable energy sources to supporting a portion of total energy consumption (Kazi, Md. S. 2021). Net load principle is described by equation (1):

$$NL = L_D - (W_P + PV_P) \tag{1}$$

Where: NL is the net-load, L_D is the load demand, W_P is the generated wind power and PV_P is the generated photovoltaic power.

Given that solar and wind power are major contributors to hybrid energy systems, and considering their variability, intermittency, and limited predictability, this will increase uncertainty in electricity grids, particularly those with high solar and wind penetration (Sandeep, K. 2018). In this case, the net load time series will become more volatile than the load time series. Since load and net load forecasting are primarily based on their respective time series, the question arises as to whether the accuracy of the forecast varies or remains constant. In other words, should power system companies rely on the same forecasting methods even as wind and solar energy usage increase?

To the best of the authors' knowledge, no other study has addressed this question. Since net load forecasting is a relatively recent field of research, this work contributes to enriching the subject by answering the posed question through using Adaptive Neuro Fuzzy Inference Systems (ANFIS) as an advanced AI-powered forecasting technique, using load, wind, and solar power data from the Spanish electricity grid to predict load and net load (Open Power System Data 2025), and to investigate how the accuracy of net load prediction is affected when significant levels of solar and wind power are integrated into the electricity grid. It has been shown that high variability in solar and wind power leads to greater error in net load forecasting compared to actual load. Clearly, the transition from actual load forecasting to net load forecasting in the renewable energy era requires additional monitoring of fluctuations in the time series of net load and addressing how to improve forecast performance to maintain an acceptable level of net load forecasting accuracy.

LITRATURE REVIEW

Net Load Forecasting Categories

Depending on the purpose of the forecast, studies have classified net load forecasting into different categories such as forecast level, forecast strategy and forecast horizon.

Net load forecasting levels range from large scales such as systems and bus levels to small scales such as buildings and household levels. For example, forecasting the net load for power systems in both Alberta (Canada) and Ireland are presented in reference (Hamid, S. 2014), the net load of a micro grid at the University of California in reference (Amanpreet, K. 2016), a net load for a feeder line of a micro grid consisting of wind turbine, photovoltaic power generation, energy storage devices and common loads in reference (Liu, J. 2014), and the net load profiles for 75 family homes equipped with solar panels in reference (Kobylinski, P. 2020).

Furthermore, net load forecasting can be categorized into two types: direct and indirect, depending on the forecasting strategy (Aburiyana, G. 2021). Direct net load forecasting relies on net load time-series to generate the forecast (Georgios, T. 2024), while indirect forecasting requires forecasting load (Nthambi, M. N. 2020), wind, and solar power separately, and then combining them to obtain the net load forecast. According to (Georgios, T. 2023), the direct net load forecasting strategy offers easier data access, as the forecasting process relies solely on the net load time series, rather than separate load and renewable energy resources data. Moreover, the direct net load forecasting strategy has a computational advantage, requiring only the training of a single model instead of multiple models as in the case of indirect forecasting. Regarding the accuracy of net load forecasting, researchers are still investigating which of the two strategies achieves better accuracy. However, (Aburiyana, G. 2024) concluded that the accuracy of net load forecasting depends on the deployment levels of renewable energy sources, and that one net load forecasting strategy is not necessarily superior to another at all times.

As with load forecasting, net load forecasting can be categorized according to time horizon. Studies have identified three main time frames. First, long-term net load forecasting which is commonly used to forecast net load over a period of one year or more. This time frame is suitable for power generation growth planning. Second, the medium-term net load forecasting which is used to forecast net load over a period of weeks to months and is suitable for seasonal net load forecasting. Third, short-term net load forecasting which is necessary for forecasting net load over a period of hours to days. It is suitable for spinning reserve allocation and maintenance scheduling. A fourth category (added in studies) is very short-term net load forecasting, which describes net load forecasting over a period of seconds to minutes. It should be noted that the time horizon ranges mentioned above are not fixed but are approximate/average and may vary in some publications. Of these four time-horizon categories, short-term net load forecasting contributes significantly to system operations and is considered a primary source of information for all daily and weekly scheduling and generation commitments (Haq, Md R. 2019).

Net Load Forecasting Techniques and Methods

Numerous modern load and net load forecasting models have been developed for the benefit of electricity generation and distribution companies. Researchers continue to work on improving forecasting accuracy to enhance the operational efficiency of power systems and increase revenue. The scientific literature offers a wide range of forecasting techniques and methods, which are categorized according to their computational mechanism into statistical methods, artificial intelligence-based methods, and hybrid methods.

Statistical Forecasting Methods:

Traditional methods such as autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA) and seasonal autoregressive integrated moving average (SARIMA) are known for their effectiveness in dealing with linear problems and require neglecting fluctuations and noise in the original data. Therefore, obtaining accurate estimates for electrical quantities with nonlinear dynamics is challenging (Jafar, M. M. 2023).

•Artificial Intelligence-Based Methods:

These are characterized by their ability to generalize and learn independently and they can provide better forecasts than statistical methods when dealing with nonlinear problems. Examples of this class include Support vector machine (SVM), artificial neural networks (ANNs) and Long Short-Term Memory (LSTM). ANNs have been used in a wide range of applications because they do not require any assumptions, able to produce forecasts depending on historic data and can efficiently solve complex nonlinear problems (Siriwardana, K. M. M. H. 2022), (Jiang, P. 2016). However, they have been found to have some drawbacks such as complexity, slow convergence, and approximation to suboptimal solutions (Jafar, M. M. 2023).

•Hybrid Forecasting Methods:

The use of models in this category has increased, and they have contributed significantly to publications on methods for forecasting electrical loads and net loads. These models combine two or more algorithms to overcome the limitations of individual models, producing hybrid models with better prediction results than their corresponding individual models. The scientific literature is replete with a vast variety of hybrid approaches, such as those combining ARIMA or SARIMA with either LSTM or ANN. These combinations have proven their ability to accommodate both linear and nonlinear characteristics of the problem and achieve improved prediction accuracy. According to reference (Salman, A. 2024), the high efficiency of ANNs in learning from training data, and the superior performance of SVM with unstructured data, have made both of them important key contributors to hybrid prediction models.

•Adaptive Neuro Fussy Inference Systems (ANFIS)

ANFIS is an efficient hybrid forecasting technique that combines the advantages of artificial neural networks and fuzzy logic. Therefore, it is a suitable option for handling random data problems and high levels of uncertainty, such as the behavior of net load when considering the irregularity of its components (wind, solar, and load), especially during periods of high wind and solar penetration. Furthermore, ANFIS combines a “Least Square Estimator” and a “Back-Propagation Gradient Descent” methods to strengthen the learning algorithm.

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Reference (Aburiyana, G. 2024) states that ANFIS can predict net load in multiple wind and solar penetration scenarios while maintaining an accuracy of up to 97%. Some studies have considered ANFIS to be the optimal choice, outperforming regression, neural network, support vector machines, genetic models, and fuzzy hybrid systems (Barak, S. 2016).

METHODOLOGY

To forecast the load and the net load, MATLAB Fuzzy Logic Toolbox was used to train an adaptive neuro-fuzzy inference system. This technique is efficient and easy to use for loading large amounts of training data, as well as test and validation data. It also allows for specifying the type and number of membership functions and identifying the clustering technique. Moreover, it simulates the training process with the possibility of monitoring the plots of training and testing besides the error update visible.

The study used an open power system data platform, (Open Power System Data 2025) that provides European power system load, wind and solar power data in hourly time series format since early time till 2020. Spanish energy system data for 2018/2019 was used because it is complete (loss-free), eliminating the need for pre-processing. Additionally, the chosen energy system (Spain) has significant amounts of wind and solar power, making it suitable for studying a fluctuating time series of net load. Table (1) provides useful information for understanding the contribution of wind and solar power to supplying the energy system loads.

Table 1: Data summary.

		Megawatts from:			
		Load	**Wind**	**Solar**	**Net load**
Winter 2018/19	**Average**	30045	6788	792	22466
	Maximum	40107	16456	4555	37451
	Minimum	18179	584	2	9853
Summer 2019	**Average**	28981	4506	2375	22100
	Maximum	39713	13951	6323	33538
	Minimum	19572	485	32	11189

Initially, the actual net load for the selected time scale is calculated using equation (1). The target time series is then divided into two seasons: winter and summer. Going with 80% of data for training, 10% for testing, and 10% for validation, ten weeks of data are allocated to each season as follows: training data (8 weeks), testing data (9^{th} week) and validation data (10^{th} week). This results in a total of 1680 data points per season, representing 10 weeks, 7 days a week, and 24 hours a day.

AI-based forecasting techniques can understand the dependence of time-series data on input data and build a model that achieves the best possible results. Therefore, including information such as weather conditions—for example, hot days that lead to the use of air conditioning or cold days that lead to the use of heating—the day of the week, as electricity consumption varies between weekdays and holidays, seasonal factors, such as seasons known for strong winds or seasons known for high solar radiation, and economic factors, including electricity prices, average per capita income, and other factors that can affect energy consumption, net load, or both, among the inputs, contributes to improving forecast accuracy. Due to the lack of such supporting data, the input is managed to represent just five vectors containing data from the five hours prior to each actual load and net load value in the time series. This number of input vectors was chosen after experimenting with several options (from 3 to 7 vectors), but the five-vector approach yielded the best results. In addition, excluding exogenous variables enabled comparing load and net load forecast accuracy under similar conditions.

Assessment Criteria

Scientific literature includes various assessment criteria for evaluating the forecasting error. To assess the load and net load forecasting accuracy, two simple, clear and measurable criteria are used: the Root Mean Square Error (RMSE) and the Mean Absolute Error (MAE) which can be calculated according to Equations (2) and (3) respectively. It should be noticed that a third well-known error measure, namely, the Mean average percentage error (MAPE). As can be seen in Equation (4), the denominator might contain zeros or small numbers so that it is excluded. To obtain the percentage error, the resulting RMSE and MAE values are normalized to the mean of both the winter and summer samples, thus obtaining the normalized RMSE (nRMSE) and normalized MAE (nMAE), as shown in Equations (5) and (6).

$$RMSE = \sqrt{1/n \,.\, \sum_{i=1}^{n} (x_{ai} - x_{fi})^2} \tag{2}$$

$$MAE = 1/n \,.\, \sum_{i=1}^{n} \left| x_{ai} - x_{fi} \right| \tag{3}$$

$$MAPE = 1/n \,.\, \sum_{i=1}^{n} \frac{(x_{ai} - x_{fi})}{x_{ai}} \tag{4}$$

$$nRMSE = RMSE/\bar{x} \tag{5}$$

$$nMAE = MAE/\bar{x} \tag{6}$$

Where x_{ai} and x_{fi} represent the testing actual value and the corresponding predicted value, while, n refers to the testing sample size and $\bar{x}$ refers to the seasonal average value.

Results

Table (2) shows the errors in forecasting the load and net load in terms of RMSE and MAE for the two seasons: winter 2018/19 and summer 2019. The average values of the load and net load for the two seasons are also mentioned in the table to illustrate how equations (5) and (6) are used to obtain the normalized errors.

Table 2 :Resulting forecasting error

		Average (Mw)	Forecasting error			
			RMSE (Mw)	nRMSE	MAE (Mw)	nMAE
Winter 2018/19	Load	30045	682.9	2.27 %	529.3	1.76 %
	Net load	22466	820.9	3.65 %	635.5	2.83 %
Summer 2019	Load	28981	516.2	1.78 %	381.4	1.32 %
	Net load	22100	611.2	2.77 %	486.9	2.2 %

Table (2) shows a small margin of error in the load and net load forecasts, undoubtedly reflecting the outstanding performance of the ANFIS system. This is also evident in Figure (1), which shows an almost perfect match between the actual and forecast values for both load and net load in both winter (a) and summer (b). In addition, The results clearly showed that the net load resulted in a larger forecasting error than the load in the two seasons and under the two assessment measures.

However, it should be noted that RMSE and MAE represent a general description of forecasting accuracy. In reality, there is some degree of error at any given moment, such that

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the net load forecasting error is higher at times, while the load forecasting error is higher at others. This fact can be understood from Figure 2, which illustrates the relationship between the net load forecasting error (NLFE) and the load forecasting error (LFE) over the entire week of testing in both winter and summer. The figure also illustrates how errors fluctuate around zero, with each performing at varying levels and alternating overtaking each other.

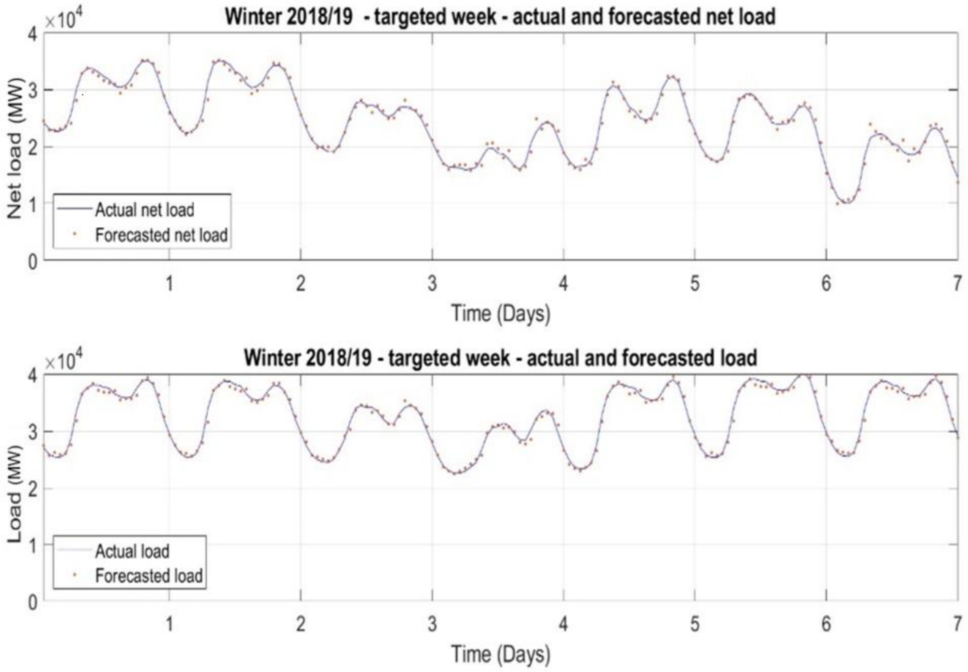

Figure 1.a: Winter 2018/19 actual and Forecasted load and net load, Spain.

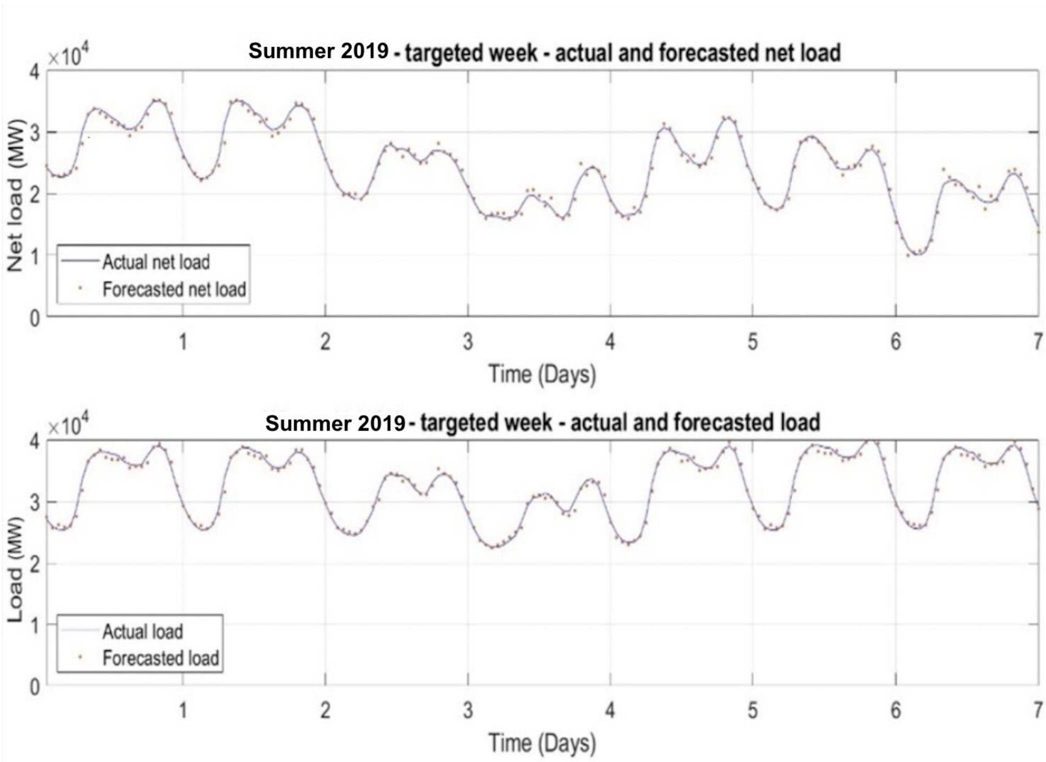

Figure 1.b: Summer 2018/19 actual and Forecasted load and net load, Spain.

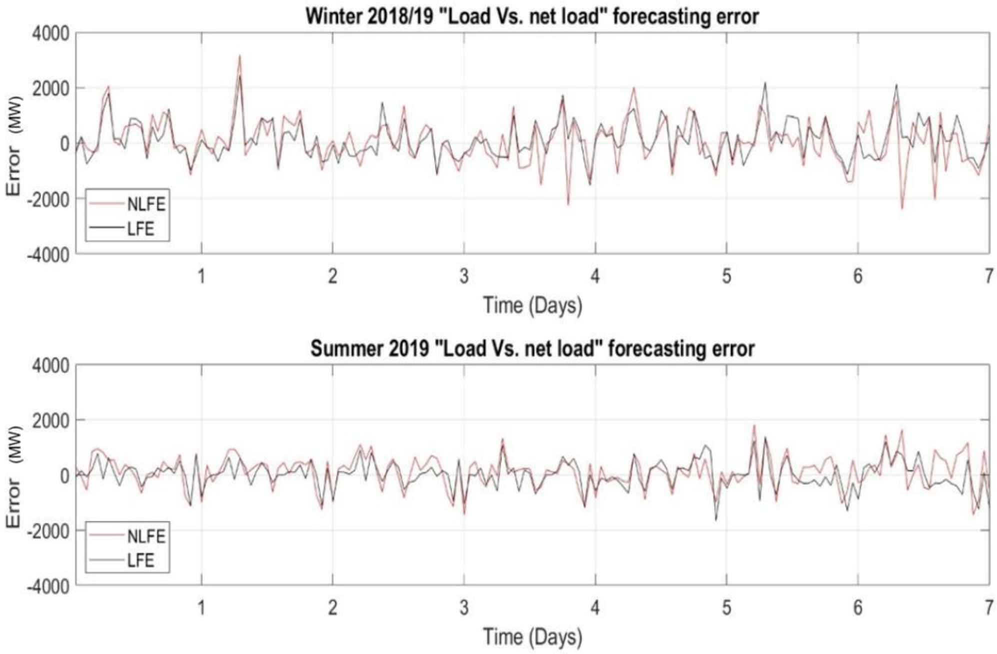

Figure 2: Load Vs. net load instantaneous forecasting errors over the testing domain.

Conclusion and Recommendations

Electricity companies are striving to develop load forecasting methods that offer the highest possible accuracy, given its importance in ensuring the reliable and economic operation of power systems. At the same time, the pursuit of global greenhouse gas emission reduction targets has led to a steady increase in the use of renewable energy resources in power systems. Among current renewable energy sources, solar and wind power are the most significant contributors. However, these are not readily available for distribution and must be injected directly into the grid to meet as many loads as possible, with conventional generating units covering the remaining loads, i.e., net load. This reality has led to a shift from load forecasting to net load forecasting, and consequently, a pursuit of the highest possible accuracy in net load prediction.

This research considers the feasibility of using a load forecasting method for net load forecasting and examines the viability of this approach by comparing the resulting accuracy levels. The study used Adaptive Neuro Fuzzy Inference Systems (ANFIS) as an efficient AI-based technique to predict both load and net load using real data from the Spanish power grid. Employing the root mean squared error (RMSE) and the mean absolute error (MAE) as evaluation criteria, the results showed that, when using the same forecasting technique, the error in predicting net load exceeded the error in predicting load. This decrease in net load forecasting accuracy is attributed to the increased volatility in the net load time series derived from intermittent renewable energy sources. This finding is significant for electricity companies when planning the integration of additional wind and solar power into the grid. To maintain an acceptable level of net load forecasting accuracy, the forecasting method should be adjusted to account for the uncontrollable amounts of renewable energy that will be integrated.

Given the importance of net load forecasting in research, which encompasses numerous aspects worthy of exploration, further work should be undertaken to improve forecast accuracy by experimenting with other forecasting techniques, including optimization methods, and incorporating supporting input data. Additionally, studies should simulate net load scenarios representing the future global share of renewable energy required and examine their impact on net load time series as well as how to manage the resulting volatility in terms of forecasting and power system flexibility.

List of Symbols and Abbreviations

ARIMA:	Auto-Regressive Integrated Moving Average
ARMA:	Auto-Regressive Moving Average
ANFIS:	Adaptive Neuro Fussy Inference Systems
ANNs:	Artificial Neural Networks
LSTM:	Long Short-Term Memory
MAE:	Mean Absolute Error
MAPE:	Mean Average Percentage Error
nMAE:	normalized Mean Absolute Error
nRMSE:	normalized Root Mean Square Error
RMSE:	Root Mean Square Error
SARIMA:	Seasonal Auto-Regressive Integrated Moving Average
SVM:	Support Vector Machine

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