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The Application of Feed - Forward Neural Network Architecture for Improving Energy Efficiency

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Abstract: The energy sector contributes approximately two-thirds of global greenhouse gas emissions. In this context, the sector must adapt to new supply and demand networks for all future energy sources. The ongoing transformation in the European energy field is driven by the ambition of the European Union to reach the climate objectives set for 2030. The main actions are increasing renewable energy production, adapting transition fuels like natural gas to reduce emissions, improving energy efficiency across all economic sectors, prioritizing building, transportation, and industry, developing Carbon Capture and Storage technologies, and ensuring universal access to clean and affordable energy. The significant changes envisaged in the energy sector to increase renewable energy production and consumption require improved integration and more use of predictive tools to support stakeholders' decision-making processes. This article presents a case study to assess the performance of predictive models based on a Feed-Forward Neural Network architecture that employ Root Mean Squared Propagation as their optimization function in terms of choosing the most appropriate activation function for this kind of data input and output. The training and testing phases of the models use data about building energy 2 consumption. The lowest training time and Root Mean Square Error values were similar for Rectified Linear Unit and Tanh activation functions. The model with the Rectified linear Unit activation function performed best.

Keywords: *Feed – Forward Neural Network; Energy Consumption; Prediction Models; Building Energy;*

JEL classification: O13, Q47.

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Introduction

The ongoing transformation in the European energy field is driven by the ambition of the European Union to reach the climate objectives set for 2030. The pace of change is influenced by the economic power of the states, the political climate in Eastern Europe, the technological challenges raised by using more of the renewable sources and the need for experts and specialists to coordinate this massive change, given that the energy field is highly regulated and particular to each state. The importance given to the production and consumption of energy is so great due to its core role in our modern society: this sector is contributing to two – thirds of global greenhouse gas emissions (International Energy Agency, 2020). The energy field is in a transition state from the fossil fuels sources renewable energy sources, such as biomass usage, wind or solar energy and other green fuels. However, the common challenge for each source of energy of the future resides in the need for the whole sector to adapt to new supply and demand chains. The main directions of action refer to: increasing the production of energy from renewable resources, adapting the usage of transition fuels such as natural gas in a way that has minimum emissions, improving the energy efficiency across all economic sectors but prioritizing building, transportation and industry, then by developing Carbon Capture and Storage technologies and ensuring universal access to clean and affordable energy.

The energy sector is the backbone of modern economy and the transition raises many complex problems that need to be addressed accordingly to each particular activity field. The intersection of the development of technologies related to the Internet of Things and the great processing capacity of data that computers have nowadays enable the main entities in the energy sector to access helpful results obtained by applying advanced statistical analysis. This kind of results can provide valuable insights to decision – making actors, specialists and important representatives in the energy field who have a significant impact in the transformative processes of this economic sector. For instance, in the present context, multiple sensors and smart meters are available to be installed on the energy supply and demand chains in order to collect data and process it to monitor the grid load and manage the production of energy accordingly.

In this paper, the focus is on the usage of advanced statistical methods to increase the predictability of energy consumption. Predictive instruments are useful for planning the activity of the plants, assess the future need of energy for a certain region and period and provide support for the experts and managers in dealing with the variability of the main renewable energy sources, wind power and solar radiation.

Artificial Neural Networks (ANNs) have a high potential to be a key tool in the future landscape of energy producers and suppliers as they have the capacity to process great amounts of data in order to predict the future demand for various lengths of time. In a context of higher variability and greater fluctuations to be managed, these methods could support to can change the energy sector by meeting the increased need of predictability in the areas of supply and demand management.

ANNs are being used in energy in a variety of areas, from forecasting energy consumption to optimising network operations and improving energy efficiency. By using historical energy consumption data and other relevant data, such as weather or economic activity data, ANNs can be trained to make accurate forecasts of short and long-term energy consumption. These forecasts can help grid operators better plan their operations and optimise their resources. Then, by analysing energy flow data, equipment status and other relevant data, ANNs can identify patterns and trends that can be used to improve the efficiency and reliability of operations. For example, ANNs can be used to identify when preventive maintenance of equipment is needed to minimise interruptions in power supply.

In this paper, it is presented a study case that considers energy consumption data from a building that are used as input for train and test ANN – based models. The outcomes of the different models will be measured and compared. The base is built on a Feed-Forward Neural Network architecture that employs a Root Mean Squared Propagation function as an optimizer. The performance of the resulted models is evaluated by taking into consideration three essential indicators: R- Squared, training time and Root Mean Squared Error. Finally, the learning curves for the most representative models are presented and discussed in order to observe the optimal choices of algorithms in the case of a dataset containing building energy consumption recordings.

Literature review

Electricity use is one of the most important areas in the energy sector and has received increased attention when talking about climate action initiatives that are underway. The construction part is responsible for more than a third of the global energy consumption and almost 40% of the total emissions (both direct and indirect) of greenhouse gases. Current figures may increase significantly to triple by 2050.

According to the literature studied to date, the operation, control and energy modernization of buildings have attracted increased attention for their need to grow their building energy efficiency and reduce associated GHG emissions, according to (Haibo, et al., 2022; Karunathilake, et al., 2018). For example, in Canada, buildings are responsible for 12% of total GHG emissions (Government of Canada, 4 2022). The government has implemented several policies and standards to help the energy performance of buildings as a result of growing concern about energy use in buildings and their associated emissions. The British Columbia Energy STEP Code (BCESC) was brought in with the goal of reducing 80% of energy consumption for new buildings by the year 2032 (Government of British Columbia, 2018).

However, the lack of directives aimed at promoting energy efficiency associated with existing buildings is the biggest challenge for reducing GHG emissions. Existing old buildings generally consume much more energy and produce more GHG emissions due to the wear and tear of less energy-efficient building materials and equipment (Prabatha, et al., 2020). We can draw the conclusion that the energy upgrades of buildings have been identified as key to success when we talk improving performance in terms of energy existing buildings and achieving the climate change improvement goal. Moreover, energy modernization can offer other benefits, as we can see: reduced utility bills and increased thermal comfort. Usually, building energy modernization measures can be divided into two groups: demand-side measures and supply-side measures (Zhang, et al., 2021).

ANN-based methods are now accepted as an alternative technology option. It provides a method to solve complex and ambiguous problems. They aren't traditionally arranged, but they are trained on previous historical data that belongs to the system of the one that they have. It has been used in many different applications. The results analysed in these papers demonstrate the potential of ANNs as a design tool in many fields, including construction.

Among the multitude of machine learning algorithms, the techniques based on ANNs have been accepted and appreciated as one of the best approaches for evaluating retrofits for building envelopes and energy-type systems and determining new optimal retrofit solutions (D'Amico, et al., 2019). We can analyse the case of (Thrampoulidis, et al., 2021) who developed an ANN-type model for the evaluation of various measures to modernize the city. This model was also tested by a study in the city of

Zurich in Switzerland. The results obtained from the study indicate that the proposed method has the possibility to substantially reduce the calculation costs without losing the accuracy for the modernization dimensions.

Similarly, (Zhichao, et al., 2019) developed a decision support tool based on ANN to evaluate energy performance and renovation actions for non-residential buildings in southern Italy. The results demonstrated that the model can be used to predict the energy performance, but also the first selection for modernization measures. Also, on this topic we find (Seyedzadeh, et al., 2020) who proposed a data-driven model to provide fast and accurate energy load forecasting. The model can be used as an ideal tool associated with decision-making tasks related to the energy modernization planning of the building.

Haibo, et al., 2022, published a review focusing on the main energy prediction methods for buildings (Mathieu, et al, 2019). Specifically, the authors compare statistics, machine learning and physics-based models. They noted that models based on machine learning scored the highest accuracy, standing out compared to statistical models. However, the developed performance exceeds the ANN models. The same approach is taken by Amasyali & El-Gohary, 2018, who explored the use of Artificial Intelligence (AI) models for building energy forecasting, but also prediction. They noted that most of the researches developed the AI-type models with usage measurement data in their case studies. ANN models have been found to be implemented in roughly a two to one ratio compared to vector machine learning algorithms.

Wei, et al., 2018, provided in 2018 a review of data-based approaches for both prediction and classification in construction. The authors of the article have observed a varied range of practical applications of ANN-type models to date, including the forecasting or prediction of energy loads, the stability of a building's current energy performance, and the anticipation of potential energy savings through retrofit strategies. Their analysis concluded that ANN prediction models were applied to a commercial building targeting a total energy load and with a short time horizon. The paper by Aydinalp, Ugursal, & Fung, 2004 looks at energy consumption forecasting and uses an artificial neural network approach in the paper to model residential energy consumption for end use at the national and regional level. Artificial neural networks have proven to be able to very accurately simulate the behaviour of houses, lighting and energy consumption and can also be used for space cooling in residential areas. As a follow-up to modelling residential end-use energy consumption using the ANN approach, two ANN-based energy consumption models were developed to estimate domestic hot water consumption and space heating energy consumption in the Canadian residential sector (Mihalakakou, et al., 2022). Time series modelling and estimation of energy consumption of residential buildings in Athens, Greece, used a neural network approach. The inputs used are several climate parameters. Building heating and cooling energy consumption values were estimated over several years using a back-propagation neural network. Various neural network architectures have been designed and trained to estimate the production, actual energy consumption of a building. The results are tested on an extensive set of non-training measurements and have been shown to agree with actual values. In addition, the "multi-lag" output predictions of ambient air temperature and total solar radiation were used as input to the neural network model to model and predict future energy consumption values with sufficient accuracy.

Tian, et al., 2019, applied in their work the Bayesian network model to identify the most energy efficient cooling system. The Bayesian model was trained using energy efficient real estate data. The trained model was then used to determine the cooling systems in the buildings. Following their analysis, the applicability of data- based construction projects was confirmed.

Although previously presented research has developed multiple models to predict building energy efficiency and retrofit options, few consider carbon emissions and the strong impact of costs when deciding to upgrade Canadian residential buildings. In addition, predictive models are needed for retrofitting options for existing homes, as more than 50% of homes are over 30 years old, many of which require major renovations to reduce CO2 emissions (Prabatha, et al., 2020).

The research in the energy sector transformation gains more interest each year as the climate objectives is getting closer. The ANN – based methods are greatly tested and used for various needs, both from industry and consumers.

Methodology

A feed-forward neural network (FFNN) is an ANN in which the information is transferred in one direction, from the input layer to the output layer, through one or more layers. Each neuron in a hidden layer receives input from the neurons in the previous layer and applies an activation function to the weighted sum of its inputs. The output of each neuron in a hidden layer is transmitted as input to the neurons in the next hidden layer until the output layer is reached. The output layer generates the neural network's ultimate output, which is typically a class label or a numerical value.

One of the benefits of FFNNs is their ability to model strong relationships between inputs and outputs, that makes them suitable for tasks where traditional statistical models may not perform well. This type of models is especially helpful in the complex energy system which has multiple links to the other economic sectors. Additionally, the dynamics within the sector are fast changing, adding complexity to any statistical approach aiming at capturing all the limitations and hypotheses present at a certain moment. Techniques based on ANN have the great advantage of being available to a larger group of specialists in the energy sector: the ANN learns based on the data provided in the model and the need of specific knowledge of the variables is low. However, there are other concerns to be taken into account when building an ANN – based model. For instance, FFNN models are susceptible to overfitting and require cautious hyperparameter tuning for optimal performance. In this paper, the models resulted for the FFNN architecture are assessed by comparing the values of three performance indicators, computed for each combination of parameters used, and the representation of the learning curves for the best performing.

The models are resulted by employing a Root Mean Square Propagation function as an optimization algorithm in the training part of the neural network. This algorithm retains the gradients of the model parameters and computes the moving average of the squared gradients for each of them. At each training iteration, the current gradient's square is calculated and exponentially averaged with preceding gradient squares. This aids in capturing the long-term gradient trends that are further used to adjust the learning rate. Large gradient parameters will have slower learning rates, while small gradient parameters will have faster learning rates. This adaptive learning rate facilitates faster convergence and reduces variations during the training process. In the end, the parameters of the ANN are updated using the adjusted learning rates. This process is repeated until convergence of the learning curves.

As previously mentioned, in the last part of this section, the assessment of the models will be discussed: it was made by considering four performance indicators and also the representations of the learning curves for best performing models.

Firstly, R – Squared is suitable for predicting continuous variables. When the dependent variable is continuous, R - Squared usually takes values between 0 and 1 and represents the percent of variance in dependent variable that the model corrects. When R - Squared is equal to 1, it means that the model is able to completely reconstruct the dependent variable, and when it is equal to 0, it means that the model completely fails in this task. In the following equations, R 2 represents the R – Squared metric, RSS stands for Residual Sum of Squares and TSS for Total Sum of Squares. Then the represents the value for the variable to be predicted, the predicted value of the variable for that instance i and is the mean value in the chosen sample of n number of observations.

$$R^2 = 1 - \frac{RSS}{TSS} \quad (1)$$

$$RSS = \sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (2)$$

$$TSS = \sum_{i=1}^{n}(y_i - \bar{y})^2 \quad (3)$$

Secondly, the training time is taken into consideration and used as a selection criterion because the context in which this type of methods can provide value to stakeholders is highly sensitive to timing. On one hand, the energy production from renewable sources is dependent on the periods of the day and weather conditions. Additionally, the demand of energy is fluctuating and presents specific patterns, including spikes, depending on the renewable energy source. On the other hand, a longer period of time needed to produce a result translates into greater computing costs for the entity that uses the model as a tool to guide their activity. Therefore, the speed with which a model can provide reliable results is essential. Thirdly, the best models are compared by considering the values for Root Mean Square Error (RMSE) as a performance metric. This indicator is helpful for assessing the accuracy of the model: it is a measure of the average magnitude of the errors between predicted and true values from a model (European Comission, 2019) . In Equation 4, N represents the number of non – missing data points, the actual value and the predicted one.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \hat{x}_i)^2}{N}} \quad (4)$$

RMSE was used as the standard statistical measure to measure model performance in meteorology. In the geosciences, many use RMSE as a standard measure of model error, such as McKeen, et al., 2005, while others choose to avoid RMSE and present only the Mean Absolute Error, such as Taylor, et al., 2013, Chatterjee, et al., 2013 or Jerez, et al., 2012.

The RMSE is sensitivity to outliers is the most common issue when employing this metric. In reality, both the existence of outliers and the likelihood of their occurrence are quite high. Incorporating these outliers permits an accurate reconstruction of the error distribution. In practice, there may be reasons to discard outliers that are even greater than other outliers, particularly when the sample size is small.

All in all, RMSE is a measure of prediction errors, but it must be interpreted within the context of the specific problem and other relevant factors. Therefore, in this paper it is considered alongside other evaluation metrics.

After the selection of the best performing models based on these three key metrics, the analysis continues with the presentation of those particular learning curves. This offers insights into the way those models performed not only on average, but during the whole period of training and testing.

Learning curves are some of the most used for machine learning algorithms that optimize their parameters over time, such as neural networks that aim for deep learning. A concrete example would be the accuracy of data classification: in general, a score is used that minimizes the error values of the data set, where low scores are better and indicate more learning. In short, a null value indicates that the training data set was able to learn perfectly and there were no errors. During the training period of an ANN, the state of the model can be evaluated at each step of the process. Evaluation of the training dataset is performed to find out how well the model trains or learns. Additionally, this analysis could be performed on a dataset that is not part of the training dataset. In other words, the two learning curves provide an overview of how well the model is learning on the training dataset and the testing or validation dataset respectively.

The concept of learning curves in the context of assessing ANNs is not attributed to a specific paper but rather emerged as a general concept in the field of machine learning and neural networks. It helps in understanding how the model's performance evolves during the learning process and whether the model is overfitting or underfitting the data. The analysis of learning curves helps the decision of the best performing model by observing the pace of learning which is influenced by the amount of data entries computed (Johnson & Nguyen, 2017). Several papers have demonstrated that the predictability of performance improvement increased along with a greater dataset (Hestness, et al., 2017; Kaplan, et al., 2020; Rosenfeld, et al., 2019).

In some situations, it is also common to make learning curves for multiple metrics, such as problems aimed at modeling predictive classification, where the model can be optimized according to the cross-entropy loss and the performance of the model is evaluated using classification accuracy. In this case, two plots are created, one for the learning curves of each metric, and each plot can display two learning curves, one for each of the training and validation datasets. Learning curves can be used to make the selection of parameters for the analyzed model, like the case of preliminary training and augmentation of the data output.

Nowadays, the use of learning curves to analyze the performance of ANNs and assess their learning progress is a common practice in the field. Researchers and practitioners often plot the learning curve, which shows the training and validation or test error rates or other relevant metrics as a function of the number of training examples or training iterations. Clearly, the concept learning curves applied for ANN – based models has become a widely recognized and utilized tool for assessing and analyzing the training and performance of neural network models.

Results and discussion

In this part of the paper, we compare the performance of the models resulted from training a Feed – Forward Neural Network that uses a Root Mean Square Propagation function as an optimizer. In this paper, the performance evaluation of the resulted models will be done by taking into consideration three key indicators: R – Squared, training time and Root Mean Squared Error. Additionally, the learning curves for the most representative models for each criterion will be presented and discussed.

The results of the models are obtained by training and testing the Feed-Forward Neural Network on energy consumption data, collected from a building that was made available by (Howard, et al., 2019). The predicted variable is the energy consumption, measured in kWh and described by the air temperature and pressure, cloud coverage, wind speed and orientation and precipitations level.

The first criteria taken into account when assessing the quality of a prediction result is the value for R – Squared indicator. It is useful in comparing the performance of the models by showing how much a certain model explains the variability or how well the predicted numbers from the model match the observed values. The results of the ANN – based model are presented in Table 1.

Table 1. Summary of the resulted models. Source: Author's own research.

R-Square values	Number of models	Percentage from the total models resulted
Less than 90%	259	27%
Between 90 - 95%	256	26%
More than 95%	457	47%

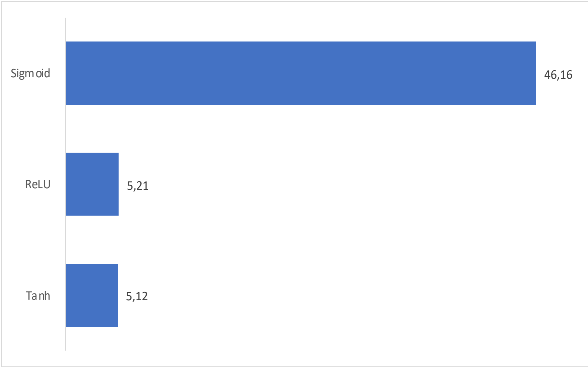
The total number of resulted models is 972 and the majority of them have above 95% statistical confidence. Even in a more general perspective, an addition 26% of the models have above 90% as values for R – Squared, which is an acceptable threshold.

Then, another insightful metric is the duration of the training for the model. The values for the training time suggests how fast a model can process new input data and produce a result. This metric is especially important in business scenarios where the need to know the predicted value immediately is high, such as the planning of operational activities or meeting the grid demand in the next hours. From this perspective, from the 972 resulted models, 824 models trained in less than a minute and 148 models had a training time higher than 60 second, meaning 85% and 15% respectively, from the total number of resulted models.

The models are trained on data regarding the energy consumption and this study case focuses on ANN – based options for modelling data with the aim of offering support for decisions for a short period of time. Given that until this point two metrics were discussed, in the following paragraphs only a selection of models will be analysed, more precisely the ones with R – Squared values higher than 95%.

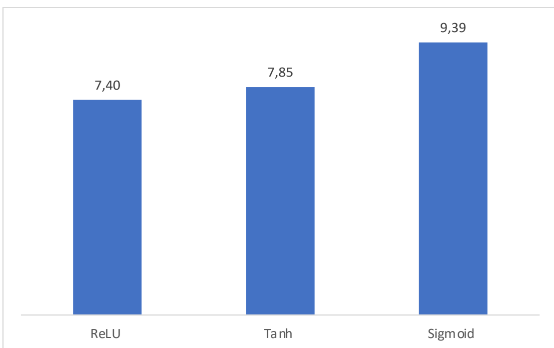
The usage of different activation functions for the models offers insights into how these algorithms influence the training time among the 457 resulted models. In Figure 1, it is represented the shortest time for training for each activation function considered. The sigmoid function is by far the worst performing in terms of training time, with a minimum value of 46,16 seconds. The Rectified Linear Unit (ReLU) and Tanh activation functions obtained close values for training time, with a difference of 10 seconds from one another.

Figure 1. The lowest training time for each activation function used in the FFNN models, with R – Squared greater than 0,95. Source: Author's own research.



Finally, a third criteria for assessing the performance of the models is the accuracy of the predicted value. This performance dimension is measured in this study case by the Root Mean Square Error (RMSE) and the results are presented in Figure 2. This metric is relevant for assessing the accuracy of a specific model by taking into account the error, defined as the difference between the predicted value and the actual data point. The comparison between the minimum values for each activation function offers insights into the way these functions impact the way errors are resented in the models. The ReLU and Tanh functions are similar again. Even if the difference is greater than in the case of the lowest training time, the 0,45 gap between the values for the two activation functions suggests they are a better fit for the FFNN architecture.

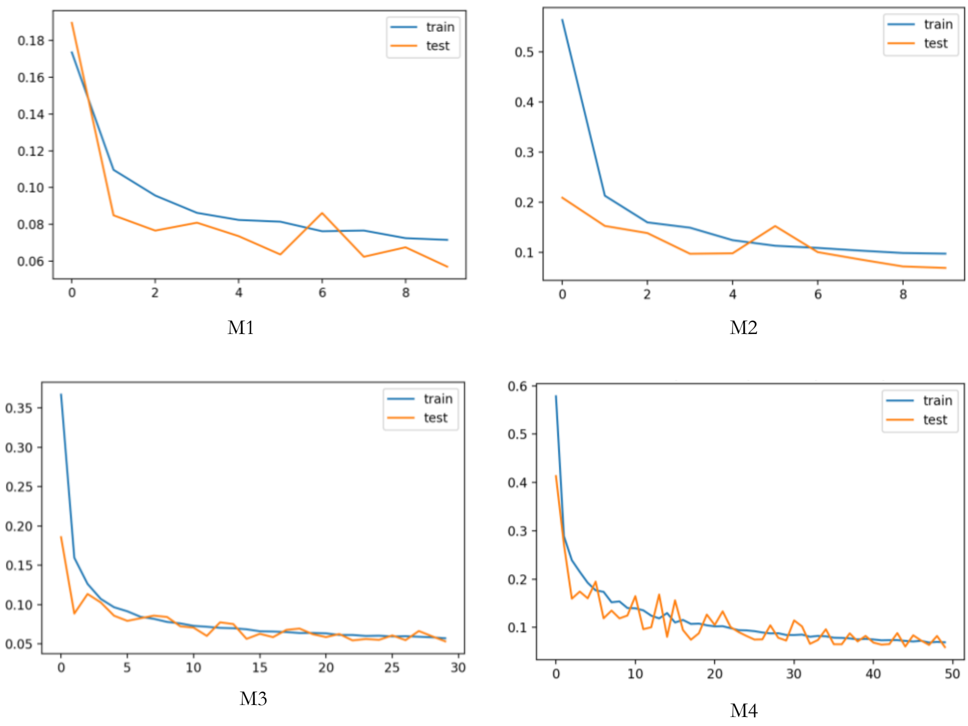
Figure 2. The minimum values for RMSE for each activation function used on the FFNN models. Source: Author's own research.



In an economic context, this error metric translates into costs and it is necessary to define the acceptable threshold for it by considering several aspects, such as the category of risks in the case of an error produced in the expected range and the scale of the impact and the associated costs for the beneficiary of the prediction model.

In the final part of this section, the learning curves for the best performing models, presented in Figure 3, will be discussed: the lowest training time for ReLU (M1) and for Tanh (M2), the minimum value for RMSE for ReLU (M3) and for Tanh (M4). The learning curves of the models are grouped by column by the type of activation function used and by row by the value of the training time.

Figure 3. The learning curves for ReLU (left) and Tanh (right) activation functions with the lowest training time (top) and minimum value for RMSE (bottom).
Source: Author's own research.



The best performing model appears to be Model 3 with the plot of testing loss decreasing to a point of stability while having a small gap with the training loss plot. Figure 3 presents the learning curves for Model 3 characterized by ReLU as activation function and the minimum value for RMSE.

Conclusions

The massive changes expected in the energy sector in order to reach a greater energy production and consumption from renewable energy sources demands a better integration and a larger use of predictive tools that can support the decision – making process of the concerned stakeholders.

Apart from their incredible computing power, the ANN techniques present a great potential in being the link towards a more sustainable and efficient energy system due to their capability of learning and making predictions based on historical data. Energy usage prediction can be complex and therefore this capacity is desirable. ANNs find meaningful patterns and relationships in data, increasing energy consumption estimates.

ANNs are better at modelling nonlinear interactions between input factors and energy usage than traditional statistical models. Weather, time of day, occupancy, and other factors such as economics, policy and consumer behaviour affect energy consumption in nonlinear ways.

ANNs can process many input variables and data types. They can incorporate multiple energy consumption aspects because they can handle numerical and categorical data. Time-series data allows ANNs to capture energy consumption seasonality and temporal relationships.

Moreover, ANNs learn meaningful features from input data without feature engineering. This type of techniques outperforms statistical models in energy consumption prediction. ANNs can make more accurate forecasts by capturing complex relationships and adapting to changing situations, improving energy planning, resource allocation, and decision-making.

This paper proposes a study case for assessing the performance of Feed – Forward Neural Network models that use Root Mean Squared Propagation as optimization function. The models are trained and validated on data regarding building energy consumption.

Rectified Linear Unit and Tanh activation functions obtained similar values both for the lowest training time and the minimum Root Mean Square Error indicator. The analysis concludes that from the resulted models, the best performing one was applying a Rectified linear Unit activation function and had the minimum value for the Root Mean Square metric.

The insights from this study case can be valuable for researching the best methods to use in real business scenarios regarding the prediction of energy consumption. Nevertheless, this model could be improved by adopting several approaches in further research: training and testing different Artificial Neural Network architectures and other algorithms, feature engineering or model hyperparameter tuning.

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