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Energy baseline model enhanced based on artificial neural network in industrial buildings

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ABSTRACT

In this article, a new energy-efficient reference model has been established for a plastic injection molding plant. However, the proposed model handled difficulties due to the lack of robust and complete data, such as production mix and cooling degree-days. In addition, the proposed model applies three distinct enhanced modeling methodologies, including regression modeling, artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS). Furthermore, these performance parameters were established to assess the accuracy of each model in this work. Moreover, the numerical results show that among the methodologies used in this work, the ANN demonstrated effective performance despite uncertainties in the measured input variables. The ANN numerical results in this paper highlight the ability to accurately assess baseline consumption in the industrial sector, providing a practical tool for decision-makers to improve energy efficiency.

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1. INTRODUCTION

Throughout the previous ten years, the debate surrounding greenhouse gas (GHG) emissions, as a consequence of global climate change and ecosystem damage, has remained a critical environmental concern on a global scale [1], [2]. However, global heating, melting ice, rise in sea levels, acidification of the oceans and extreme weather phenomena are all manifestations of climate change, and the risks to the Earth and future generations are serious; therefore, urgent and effective measures are needed to comprehensively address the peril of global warming [3]. Furthermore, to mitigate the consequences of GHG emissions, the international energy agency has proposed investments and improvements in energy efficiency for industrial plants and buildings [4].

Furthermore, in the industrial sector, projected energy demand is expected to reach 307 quadrillion Btu by 2040, up from 200 quadrillion Btu in 2010, an increase rate averaging 1.4% per year as shown in Table 1. A significant portion of the sustained increase in energy usage in manufacturing sectors is evident in regions outside the organization for economic co-operation and development (OECD) (Table 1) [5]. In industry, a few studies have investigated the opportunities for mitigating GHG emissions by enhancing energy efficiency [6], [7]. In this field, the importance of measurement and verification (M&V) protocols lies in their ability to assess the effectiveness of energy conservation measure (ECM).

A range of M&V protocols and guidelines have been defined. The IPMVP is the most frequently employed protocol for M&V performance [8] and is universally recognized as a standard reference for M&V.

In accordance with this protocol, the energy reference model plays an essential role during the planning phase of an M&V program. Among the various methods suggested for establishing reference consumption, the technical method is the easiest to apply [9]. This approach uses standard energy formulas and assumptions to calculate energy consumption prior to implementing retrofit measures. However, although simple and straightforward, the application of this approach introduces a level of uncertainty [10] and is therefore unsuitable for systematic application in the industrial sector. In this regard, many cost-effective energy efficiency measures are not being implemented due to the complexity and unpredictability of industrial energy efficiency models. In this filed, regression models offer an easier approach to use and more straightforward to interpret compared to more complex techniques. This is why they have found wide application in predicting building energy demand [11], [12]. Regression models relate energy use to external environmental conditions and internal operational parameters. Models are constructed with either actual historical data [12], [13] or simulated load data [14], [15].

Table 1. Global industrial sector energy use, categorized by region, and energy sources, from 2010-2040 (in quadrillion Btu)

Region	2010	2015	2020	2025	2035	2040	Average annual percentage charge 1990–2010	2010–2040
OECD	**71.9**	**71.9**	**77.5**	**80.4**	**82.2**	**84.4**	**87.1**	**0.6**
Petroleum and other liquids*	27.4	27.5	29.3	30.3	31	31.7	32.6	0.6
Natural gas	19.4	20.2	21.7	22.7	23.5	24.3	25.2	0.9
Coal	8.7	8.7	9	9.2	9.2	9.2	9.2	0.2
Electricity	11	11.3	12	12.4	12.6	12.9	13.2	0.6
Renewables**	5.3	5.2	5.5	5.7	6	6.3	7	0.9
No-OECD	**128.1**	**148.5**	**169.2**	**186**	**201.3**	**213.3**	**219.8**	**1.8**
Petroleum and other liquids[a]	29.8	34.1	37.1	39.8	43.2	46.5	49.5	1.7
Natural gas	26.1	28.7	32.6	36.3	40	43.6	46.6	2
Coal	44.2	53	61.1	67	71	72.6	70.4	1.6
Electricity	18.2	22.9	27.4	30.9	33.9	36.1	36.8	2.4
Renewables*	9.9	9.8	10.9	12	13.3	14.8	16.6	1.7
World	**200**	**221.4**	**246.7**	**266.4**	**283.5**	**297.9**	**306.9**	**1.4**
Petroleum and other liquids[a]	57.2	61.6	66.4	70.1	74.2	78.2	82.1	1.2
Natural gas	45.5	48.8	54.3	59	63.4	67.8	71.7	1.5
Coal	52.9	61.7	70.1	76.2	80.2	81.9	79.6	1.4
Electricity	29.2	34.2	39.4	43.3	46.5	49	50	1.8
Renewables**	15.2	15	16.5	17.7	19.2	21.1	23.5	1.5

* Additional liquids include both natural gas liquids, produced through the Fischer–Tropsch process.
** Incorporates biomass employed for cogeneration purposes, along with biomass designated for process heat.

Recently, a growing number of academics have been using artificial intelligence (AI) algorithms to forecast energy demand and other fields. Kumar *et al.* [16] use a multi-behavior detection model, derived from new transaction behavior, from which further models can be developed. Furthermore, Agasti and Satpathy [17], predict customer churn in the telecom field with the Naïve Bayes algorithm. For forecasting energy in different countries, the case of Turkey, Pabuçcu *et al.* [18] implemented adaptive neuro-fuzzy inference system (ANFIS) to forecast primary energy use from 2016 to 2030. In addition, Hamzacebi [19] used an artificial neural network (ANN) to predict electrical energy consumption by sector to 2020. In Uganda, Kasule and Ayan [20] developed a model based on ANFIS approach to forecast electricity consumption. In Morocco, Zaaoumi *et al.* [21] have used ANFIS and ANN models to assess the energy production of a solar installation. As natural gas demand predicting is also essential in the energy sector, several studies have applied different models to predict this latter. Azadeh *et al.* [22] introduced an ANFIS model specifically designed to forecast natural gas demand.

Furthermore, development of a simplified and accurate energy model is the key step towards enhancing the energy efficiency of industrial plants. In this case, the objective is to support manufacturing factories in implementing energy-saving measures. This paper introduces a novel methodology for an operational energy reference model in a plastic injection plant based in Casablanca (Morocco), which currently suffers from a lack of robust and comprehensive data (e.g., production mix and environmental factors like cooling degree-days).

The objective of this manuscript is to investigate the accuracy of ANNs in improving M&V processes in industrial buildings. The suggested methodology has been established by comparing the complexity and accuracy of energy input models using ANNs, ANFIS, and linear regression in a plastic injection factory in Casablanca, Morocco, which has been chosen as the experimental site for the proposed methodology. The experimental results achieved in the process demonstrated a high degree of efficiency towards 80% and exceeded requirements at the plant investigated in this work. The paper is structured as follows: ASHARE and IPMVP protocols are highlighted, also linear regression, ANFIS and ANNs are detailed in section 2. In section 3 elaborates the numerical results with discussion followed by a comprehensive conclusion in the final section.

2. MATERIALS AND METHODS

Currently, M&V involves the systematic planning, measurement, collection and analysis of data to authenticate and document the energy savings achieved in a specific facility through the implementation of ECM [8], [23]. In this regard, economies are calculated by comparing consumption recorded before and after project implementation, making any necessary adjustments to account for changing conditions [23]. As an illustration, Figure 1 highlights energy consumption during the reference period and after the renovation.

Typically, the pre-retrofit period referred to the period preceding the installation of the retrofit, on the other hand, the post-retrofit period referred to the period following the ECMs implementation. In line with the IPMVP protocol, the M&V calculation involved the initial development of a reference energy model. This model aimed to establish the correlation between energy consumption and independent variables through regression analysis. Next, the model was used to forecast the energy demand that could have taken place without modernization efforts. This prediction, known as the adjusted reference energy, was then compared with actual energy demand during the post-retrofit phase in order to quantify the achieved energy savings [8], [23].

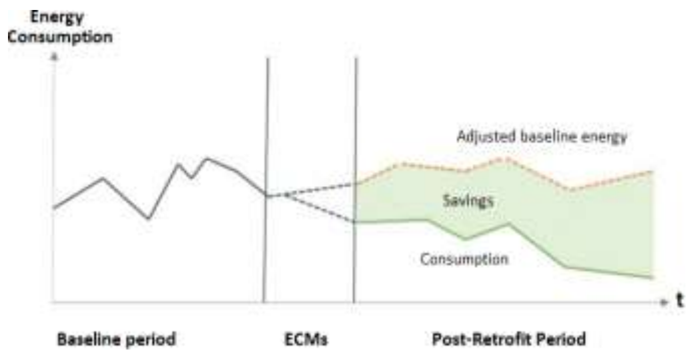

Figure 1. M&V conceptual structure

2.1. Regression analysis

Although a statistical method that reveals the relationship between several variables, which are often represented graphically. This approach evaluates the correlation between a dependent and an independent variable. As outlined in the ASHRAE guidelines, the approach is summarized as a mathematical method involving the derivation of factors from a data set in guideline form to clarify the correlation between observed independent and dependent parameters, usually involving energy-related values [24]. Since its founding in 1894, ASHRAE has been committed to improving building systems through research, the development of standards and the publication and informative resources.

2.1.1. Simple regression

The formulation for the simple linear regression model is:

$$y = \beta_1 + \beta_2 X_1 \quad (1)$$

this equation is structured in the following manner: y represents the dependent variable value, β1 signifies the parameter determining the y-intercept, β_2 denotes the parameter characterizing the linear relationship with the independent variable, and X_1 corresponds to the value of the independent variable.

2.2. Artificial neural networks approach

The neural feed-forward model is a fundamental form of ANN and involves a unidirectional flow of information. This indicates that data moves from the input layer through the hidden layers, eventually reaching the output layer. This is the most basic and widespread neural network architecture. Generally organized in layers, this structure is commonly referred to as a multilayer perceptron (MLP) [25]. Figure 2 provides an illustration of a feed-forward neural network. Within a neural network, every node serves as a computational element housing a weight and summation function, succeeded by a nonlinearity, as depicted in Figure 3.

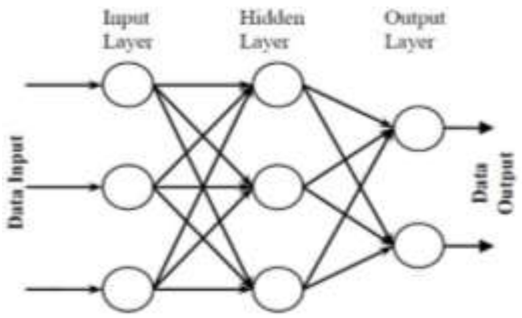

Figure 2. Essential layout of a MLP

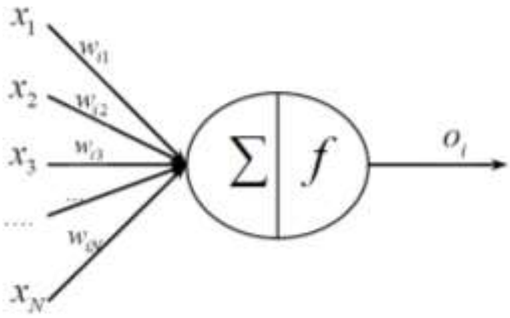

Figure 3. Single neuron with N inputs

The associated calculation can be expressed as (2):

$$O_i = f(\sum_{j=1}^{n} w_{ij}\, x_j) \tag{2}$$

here, O_i denotes the neuron i output, f(.) represents the transfer function, w_{ij} signifies the connection weight between neurons i and j, and x_j is the neuron j input signal. The overall training process for the network involves three main steps: passing the input signal through the network, propagating the error backward, and refining the weights. The backpropagation algorithm aims to enhance the neural network's performance by minimizing the total error, calculated as (3):

$$E = \frac{1}{2}\sum_p \sum_j \left[O_{jp} - d_{jp}\right]^2 \tag{3}$$

in this formula, E is the mean square value, p is the maximum number of neuron patterns implemented, d_{jp} is the expected output of the jth neuron when the pth is selected, and jp is the target output of the jth neuron.

2.3. Adaptive neuro-fuzzy inference system

ANFIS is a neural network designed for adaptive learning. Introduced by Jang in 1993 [26], it integrates neuro-fuzzy principles with a learning algorithm. This system is adept at handling nonlinear data, commonly encountered in real-world applications, by transforming a nonlinear input vector into scalar outputs. One of the strengths of the ANFIS is its ability to use numerical values as well as verbal expressions [27]. The ANFIS framework relies on if-then rules, represented by 'if x is alpha and y is beta then z=(x, y),' where alpha and Beta represent fuzzy labels, and f is a crisp function. Additionally, it incorporates input-output data processing and undergoes training through the application of an ANN learning algorithm.

The ANFIS architecture has five layers: fuzzy, product, normalised, defuzzification, and output layers [28]. It can be described as follows [26]:
- In the initial layer, membership functions are employed, with triangular and bell-shaped functions being the most prevalent.
- The second layer is tasked with producing the firing strengths corresponding to the defined rules.
- The third layer presents outputs called normalised strengths.
- In the fourth layer, the calculated firing strengths undergo normalization, achieved by dividing each value by the cumulative firing strength inputs. The outcome is the normalized strength denoted by 'w.'
- The fifth layer calculates the simple sum of the outputs from the fourth layer.

2.4. Performance metrics

2.4.1. Coefficient of variation of the root mean square error

The extent of errors' variability in the recorded and modelled data is assessed, offering insights into the model's capability to accurately forecast the general load pattern evident within the dataset [29]. This metric serves as a measure to quantify modelling errors, aligning with both the ASHRAE guidelines [24] and the IPMVP [8], [23]. The formula for this metric is outlined as (4):

$$CV(RMSE(\%)) = \frac{1}{\overline{m}}\sqrt{\frac{\sum_{i=1}^{n}(m_i S_i)^2}{n-p-1}} * 100 \tag{4}$$

in (4), m_i signifies the observed or actual value, S_i represents the forecasted value, $\overline{m}$ denotes the average actual value, p represents the explanatory variables number considered in the model, and n corresponds to predictions number made during the analysis period.

2.4.2. Coefficient of determination (R^2)

This metric reflects the degree to which the forecasted values align with the regression line of the observed values. This statistical metric serves as a common indicator for assessing model uncertainty. Ranging between 0.00 and 1.00, a greater value reflects a stronger correspondence between simulated and measured values, while smaller values indicate a less favourable alignment. The ASHRAE Handbook [24] and IPMVP [8], [23] both advocate for a coefficient of determination (R^2) in calibrated models to be consistently above 0.75.

$$R^2 = \left(\frac{n\sum_{i=1}^{n} m_i S_i - \sum_{i=1}^{n} m_i \sum_{i=1}^{n} S_i}{\sqrt{(n\sum_{i=1}^{n} m_i{}^2 - (\sum_{i=1}^{n} m_i)^2)(n\sum_{i=1}^{n} S_i{}^2 - (\sum_{i=1}^{n} S_i)^2)}}\right)^2 \tag{5}$$

This metric is defined as the proportion of the explained variation to the total variation:

$$R^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST}\, R^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST} \tag{6}$$

here,
– SSR signifies the explained variation:

$$SSR = \sum_{i=1}^{n} (\hat{y}_i - \bar{y})^2. \tag{7}$$

– SST signifies the global variation:

$$SST = \sum_{i=1}^{n} (y_i - \bar{y})^2. \tag{8}$$

where yi is the observed value, and $\bar{y}$ is the mean of the observed value.
– SSE signifies the residual variation:

$$SSE = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{9}$$

where $\hat{y}_i$ is the predicted value from the model.

3. RESULTS AND DISCUSSION

In this section, experimental and computational simulation results are analyzed to comprehensively evaluate model performance, the evaluation criteria have been kept consistent with those specified by Zhao and Magoules [11] under the same conditions:
– No ECM was performed in the manufacturing plant during the analysis period.
– During the analysis period, there were no alterations to the building characteristics.

3.1. Data collection process

The proposed case study in this work involved a plastic injection plant based in Morocco, dedicated to the production and marketing of electrical components. The site occupies an area of 15,000 square meters and has a workforce of over 700. The analytical work utilized a dataset covering 29 months, with the purpose of forecasting the fundamental energy model (y) as a function of plant production. The most complex aspect of this case of study is the fact that the only data available was that of production in tonnes. The dataset yielded 29 observations, as illustrated in Table 2.

Table 2. The dataset used in this study

Date	Metallic parts	Consumption (kWh)
January 17	20,542	807,280
February 17	19,003	789,337
March 17	21,517	827,477
April 17	22,959	792,416
May 17	20,965	833,008
June 17	20,377	742,018
July 17	17,390	709,626
August 17	21,494	775,199
September 17	10,613	423,766
October 17	14,964	646,502
November 17	20,427	803,569
December 17	22,079	858,310
January 18	22,485	813,176
February 18	19,539	739,084
March 18	20,814	760,202
April 18	20,708	718,782
May 18	19,370	693,324
June 18	11,891	505,661
July 18	20,194	716,072
August 18	19,836	708,668
September 18	18,939	669,566
October 18	19,903	701,955
November 18	19,860	769,570
December 18	19,776	786,366
January 19	20,045	795,384
February 19	18,840	761,426
March 19	19,862	822,813
April 19	20,017	797,213
May 19	21,120	516,649

3.2. Results of the SLR, ANN, and ANFIS

3.2.1. SLR model

To forecast the energy demand, the regression equation provided in (10) is employed.

$$Y = 28.54\,x1 + 177{,}362 \tag{10}$$

The regression analysis results are presented in Figure 4.

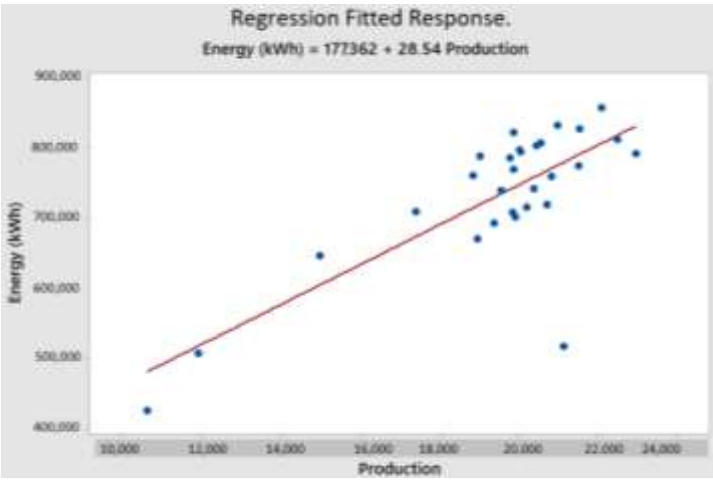

Figure 4. Regression fitted responses versus the corresponding targets

3.2.2. ANN model (feed forward neural networks)

The feed-forward neural network is a fundamental type of ANN, characterized by a unidirectional flow of information. Data progresses from the input layer, through the hidden layers, and ultimately reaches the output layer. This represents the most basic and widely used architecture in neural networks. In this architecture, nodes are connected by weighted connections and use an activation function to propagate their signals to the output layer. It is recognized as an effective network for curve fitting and is considered one of the more robust models that does not require a validation process. Several configurations were trained, and the optimal architecture developed using MATLAB is illustrated in Figure 5. As shown in Figure 5, the input of the ANN framework is the metallic part, and the output is the electrical power consumption.

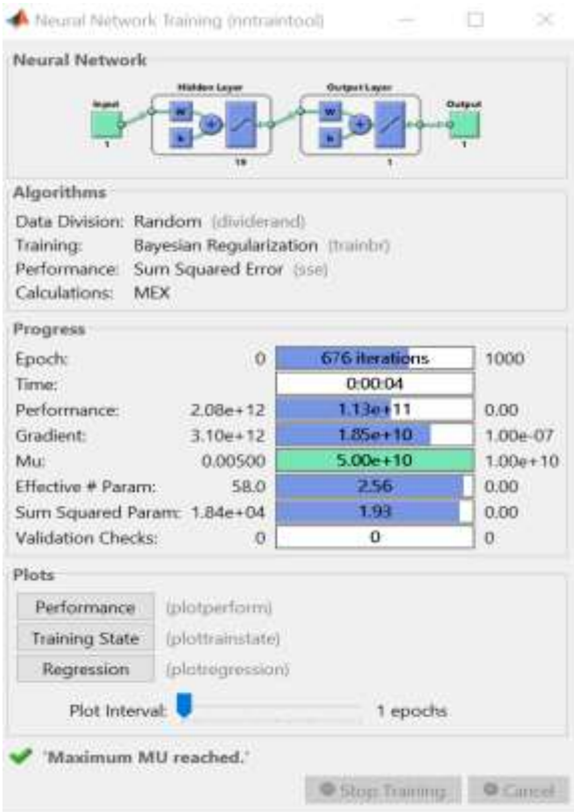

Figure 5. ANN structure

3.2.3. ANFIS model

This work developed an ANFIS model in MATLAB to forecast the plant's energy requirements, based on Sugeno's fuzzy inference algorithm. The model includes an input variable, "production", and an output variable, "energy demand". Figure 6 describes the architecture of the suggested model.

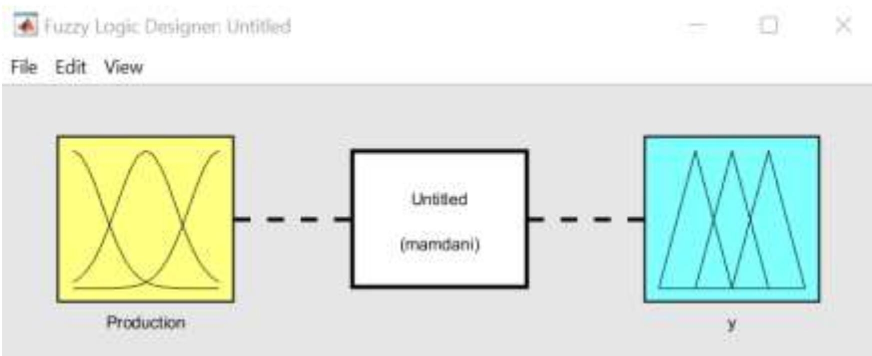

Figure 6. ANFIS model

3.2.4. Forecasting accuracy evaluation

Table 3 summarises the R^2 and root-mean-square error (RMSE) results for the developed energy baseline models. In the linear regression analysis, the coefficient was lower than 75% because of poor data quality. Following the IPMVP, managers must go deeper and analyse other explanatory variables. The accuracy of the energy model is again a clear barrier for decision makers. However, production reports provide data on the mix and quantities, which means that managers need to look for external explanatory variables, such as cooling degree days, traceability of the production mix, to confirm the business case.

The ANFIS model boosted the effectiveness of the regression model by 30% (R^2=69.26%). However, poor data quality prevented us from obtaining an R^2 value higher than 75%. The M&V project team must always search for other explanatory variables, which is complicated. Thus, the ANN provided a model with a higher R^2>97% and a lower CV(RMSE)<8%.

Table 3. Comparative analysis of constructed models

Model	R^2	RMSE
Regression	53.44%	8.92%
ANFIS	69.26%	8.81%
ANN	97.86%	7.70%

However, the ANN model provided an accurate and simple model in which other explanatory variables were unnecessary. This paper outlined a performance measures R^2 and CV(RMSE) which demonstrated that the neural model not only provides a simple concept for defining the basic energy model, it also provides greater accuracy than the ANFIS and linear regression models. Figure 7 offers a detailed comparison of the different models. The energy reference models generated show that the ANN model represents the most accurate results compared with the other models, and for linear regression, and the ANFIS system: they behave in a similar way with higher reliability for the ANFIS model.

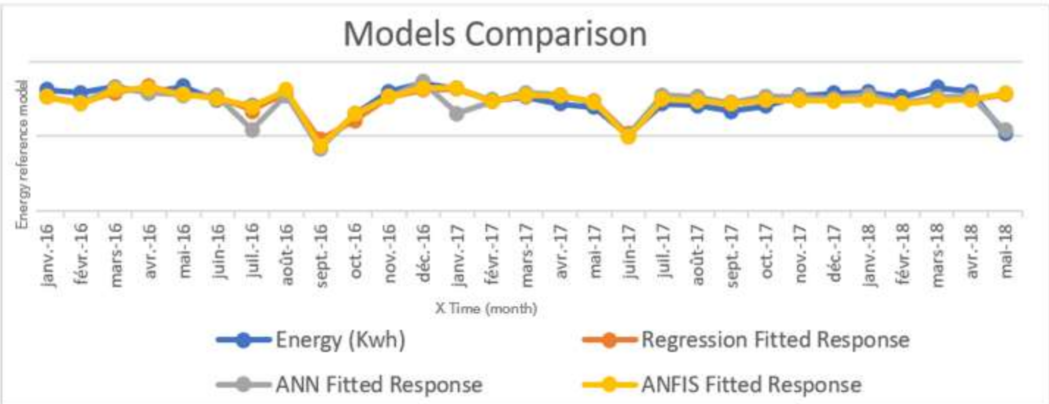

Figure 7. Comparison among the ANN, linear regression, and adaptive neuro-fuzzy inference system

4. CONCLUSION

This paper has developed a new analysis process based on linear regression, ANN and ANFIS models to evaluate demand for energy in a manufacturing plant characterized by a lack of data (cooling degree-days and traceability of the production mix). In this respect, numerical simulations are reported using production (in tonnes) as an Input parameter and energy consumption as an output parameter. However, model performance has been assessed on the basis of the statistical indicators R^2 and CV(RMSE). Moreover, the calculated R^2 and CV(RMSE) values obtained with ANN are 97.86% and 7.70% respectively. Whereas the R^2 and CV(RMSE) of the ANFIS model are 69.26% and 8.81% respectively, and those of the regression model 53.44% and 8.92%. Consequently, the ANN-based model outperforms both the ANFIS and regression models for estimating energy demand in similar manufacturing plants. Furthermore, the results obtained indicate that ANNs are more practical than linear regression and ANFIS for modelling basic energy demand, and have the greatest potential for supporting energy efficiency projects in industrial buildings. Future work will focus on the structural design and factor optimization of this approach, as well as validation tests in real industrial buildings.

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