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Artificial Neuron Network-Based Prediction of Fuel Consumption in Antananarivo

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Abstract— *The ability to modeling fuel consumption forecast is important to improve fuel quantity suitable for users (individuals, businesses, etc.) to prevent fuel shortages. Kerosene, super fuel and gas oil consumptions forecasting models for Antananarivo region were developed. Model is based on Artificial Neural Network (ANN) learning which used advanced machine learning techniques using backpropagation algorithm. Successful time series and trend patterns given by the three ANN prediction models were presented. To predict 18 months fuel consumption in Antananarivo, ANN models' accuracy reaches more than 95% accuracy.*

Keywords— ***ANN prediction, Antananarivo forecasting model, fuel consumption, modeling***

I. INTRODUCTION

According to many researchers, fossil energy remains the most consumed on the planet earth. But earth's reserves of fossil energy resources are limited. These resources will be exhausted before the end of the next century if no strict measure of saving fossil energy consumption applied. In Madagascar, kerosene consumption rises constantly up to 3% per year since 2012, [1]. Thus, it is important to develop predictive models to predict fuel consumption. This alternative can help to improve fuel economy, prevent fuel shortages prematurely and avoid consumption peaks or overconsumption.

Several studies developed fuel consumption prediction models, [2]-[5]. Artificial Neural Network (ANN) becomes increasingly common in predictive studies and neural machine learning is suitable for such analysis, as the model can be developed by learning the patterns of data. Based on ANN, monthly fuel consumption forecast models were developed. These models use backpropagation neural network. This method has proven to be very effective in training multi-layered neural network, [6], [7]. Indeed, such models are able to learn nonlinear mappings between inputs and outputs. Performance measurements of each model are undertaken in order to assess its effectiveness, then to carry out comparative for its validity.

Thus, three models such as Kerosene, super fuel and gas oil consumption prediction models were built to predict fuel consumption in Antananarivo using ANN. The developed models are fully connected univariate models, based on past consumption values and built with multilayer perceptron (PMC).

II. DATA OF FUEL CONSUMPTION

The database used for three models of fuel consumption forecast is the set of 318 measurements monthly data from January 1995 to June 2021 for Antananarivo city [1]. According to this database, fuel consumption over time as shown in Fig. 1 presents slight regularities and similar periodic trend for the 3 types of fuel consumption.

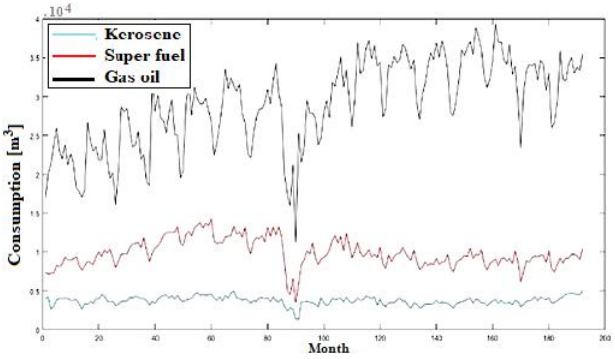

Fig. 1: Fuel consumption in Antananarivo from January 1995 to June 2021

III. PREDICTION METHODOLOGY

ANN were established as a generalization of mathematical models [8], [9], [10]. As shown in Fig. 2, ANN has a parallel and distributed processing structure. In whole, they are formed of three layers: input layer, hidden layer and output layer. Each layer has a couple of neurons. Signals are transmitted between neurons via connecting links. Each connecting link has an associated weight, which in a typical neural network multiplies the transmitted signal. Each neuron applies an activation function (usually nonlinear) to its net input (sum of the weighted input signals) to determine its output signal. The input layer of the backpropagation network consists of m units (X1, ..., Xi, ..., Xm) and one bias unit (X0). The hidden layer consists of n units (NN1, ..., NNj, ..., NNn) and a Polarization unit (NN0), while the output layer has a Y unit, which gives the value to be predicted. Polarization units have the value "1" as input signals. To build a forecasting model, the network processed three steps. First, the training step at the end of which, the network is trained to predict future data on the basis of past and present data. Second, the test step where the network is tested to stop forming or to remain in formation. Third, the evaluation step where the trained network is used to predict future data and to calculate different error measures. The number of neurons in the hidden layer is chosen according to the complexity of the function to be approximated and the performance of each model is evaluated by the RMSE and MAPE errors.

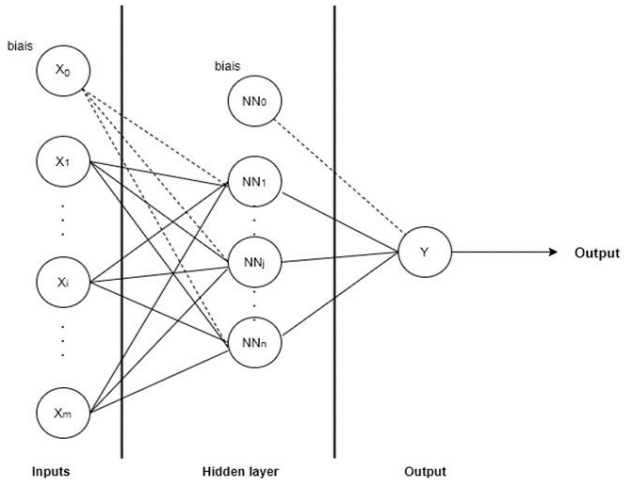

Fig. 2: ANN model for prediction

IV. MACHINE LEARNING

For machine learning, backpropagation algorithm is adopted due to its high performance in prediction, [4], [11]. This algorithm allows the input signal to be broadcast to the output layers, then the error is calculated at the output layer and propagated to the input layer. Training the network by backpropagation consists of three steps:

- Enable the propagation or feedforward of the training model from the inputs to the output,
- Calculate and back propagate the associated error,
- Adjust the weights.

During the feedforward phase, each input unit Xi receives an input signal xi and broadcasts this signal to each of the hidden units NN1; ... NNn. First, the input signal nn_inj for each hidden unit is the sum of each input signal xi multiplied by the corresponding weight wji according to the formula:

$$nn\_in_j = w_{0j} + \sum_{i=1}^{n} x_i w_{ij} \quad (1)$$

Then, each hidden unit calculates its activation function to obtain the signal nnj.

$$nn_j = f(nn\_in_j) \quad (2)$$

Same procedure is applied to the hidden layer and the output layer. Thus, each hidden unit *NNj* broadcasts its signal n_j to the output unit Y_1. Therefore, the input signal *y_in1* is the sum of each signal *nnj* multiplied by the corresponding weight w_{1j}.

$$y\_in_1 = w_{10} + \sum_{j=1}^{p} nn_j w_{1j} \quad (3)$$

Again, the output unit calculates its activation function to obtain the signal y_1.

$$y_1 = f(y\_in_1) \quad (4)$$

During this step, the input layer broadcasts the input signals to the output layer. The second step of backpropagation algorithm is the error backpropagation stage. During this stage, the output unit Y_1 calculates its error $(t_1 - y_1)$. Based on this error, the error information term δ_1 is calculated. Then δ_1 is used to redistribute the error at output unit Y_1 to all units in the previous layer.

$$\delta_1 = (t_1 - y_1) f'(y\_in_1) = \sigma.(t_1 - y_1)\, y_1(1 - y_1) \quad (5)$$

where t_1 is the output target and δ_1 is the slope parameter.

First, the factor is distributed to the hidden units using the following stage. Thus, the output unit Y_1 calculates its weight correction term, which is used to update w_{1j} later during the third stage. The weight correction term is calculated by multiplying the learning rate α with the error information term δ_1 and the signal *nnj* of the hidden unit *NNj*.

$$\Delta w_{1j} = \alpha\, \delta_1\, nn_j \quad (6)$$

Then, the output unit Y_1 calculates its bias correction term which is used to update its bias w_{10} later during the third stage. The bias correction term is calculated by multiplying the learning rate α by the error correction term δ_1.

$$\Delta w_{10} = \alpha\, \delta_1 \quad (7)$$

The following procedure is to propagate the factor δ_1 to all input units $(x_0, \ldots, x_m)$ through the following steps:

Each hidden unit $(NNj,\ j=1, \ldots,\ n)$ calculates its error by multiplying the output error information term by its corresponding weight w_{1j}.

$$\delta\_in_j = \delta_1\, w_{1j} \quad (8)$$

Then, it calculates its error information term δ_1 using the following formula:

$$\delta_j = \delta\_in_j\, f'(nn\_in_j) \quad (9)$$

Each hidden unit *NNj* calculates its weight correction term which is used to update its weight w_{ji} later in the third stage. The weight correction term is calculated by multiplying the learning rate α, the error information term δ_1 and the input signal x_i.

$$\Delta w_{ji} = \alpha\, \delta_j\, x_i \quad (10)$$

Then, each hidden unit *NNj* calculates its bias weight correction term, which is used to update its bias w_{j0} later in the third stage. The bias weight correction term is calculated by multiplying the learning rate α and the error correction term δ_1.

$$\Delta w_{j0} = \alpha\, \delta_j \quad (11)$$

Therefore, errors are back-propagated from the output layer to the input layer in order to adjust the weights between the layers.

The third stage of the learning algorithm consists of updating the weights using the weight correction terms calculated during the second stage. This procedure takes place in two steps:

- the output unit Y_1 updates its weights w_{1j} $(j=0, \ldots, n)$ using the following formula:

$$w_{1j}(t+1) = w_{1j}(t) + \alpha\delta_1 nn_j + \gamma\left(w_{1j}(t) - w_{1j}(t-1)\right) \quad 12)$$

where γ is the motion parameter.

- Afterwards, each hidden unit *NNj* $(j=1, \ldots, n)$ updates its weights w_{ji} $(i=0, \ldots, m)$ using the following formula:

$$w_{ji}(t+1) = w_{ji}(t) + \alpha\, \delta_j x_i + \gamma\left[w_{ji}(t) - w_{ji}(t-1)\right] \quad (13)$$

In this case, the network learns and improves its performance by adjusting the weights.

V. IMPLEMENTATIONS

The study covers the period from 1995 to 2021. This period is used to train, test and evaluate ANN models. Models training is based on fifteen years training set from January 1995 to December 2009, while models test covers the period from January 2010 to December 2019. In addition, model evaluation covers the period from June 2019 to June 2021. The implementations in each model use training data to predict future data using the backpropagation algorithm. Data need to be normalized between -1 and 1 using the following equation:

$$Y = \frac{(y_{max} - y_{min})(x - x_{min})}{(x_{max} - x_{min}) + y_{min}} \quad (14)$$

x assumed to have only finite real values and values in each row elements are not all equal. If $x_{max}=x_{min}$ or if x_{max} or x_{min} are non-finite, then $y=x$ and no change occur. Loaded input parameters from configuration file contains five parameters such as learning rate, momentum, sigmoid function slope value, hidden layers number, and corresponding hidden units' number.

VI. RESULTS

Since energy consumption forecast depends on the database which contains previous energy consumption, three univariate ANN models were implemented. These three fuel consumption prediction models require previous values as data input models from kerosene, super fuel and gas oil consumption database in Antananarivo. All models

are tested for a different number of network inputs and hidden units. Each model is fully connected, since each input unit broadcasts its signal to each hidden unit. It is found that too few hidden nodes in ANN does not leads to learn complicated functional models, whereas many nodes network is unable to generalize well. After performing several simulations, the best performance criteria evaluations indicated by the lowest two types of error RMSE and MAPE. Parameters displayed in this result section are selected after extensive testing by varying learning rate values and input units' number. When ANN is finally well-trained, the output parameters produce the lowest error values.

6.1 KEROSENE CONSUMPTION PREDICTION MODEL

The parameters values used in kerosene consumption prediction model producing the lowest error values are presented in Table 1. Comparison prediction results are shown in Fig. 3.

Table 1: Parameter values for kerosene consumption prediction model

ANN – kerosene consumption prediction model
Learning epoch: 5000
Optimization algorithm: SCG
CPU Time Training: 31 seconds
No. inputs 12
No. hidden units 8
Error function Sum of squares
RMSE 216.9325
MAPE 6.5860
R 0.945538703547271 (95%)

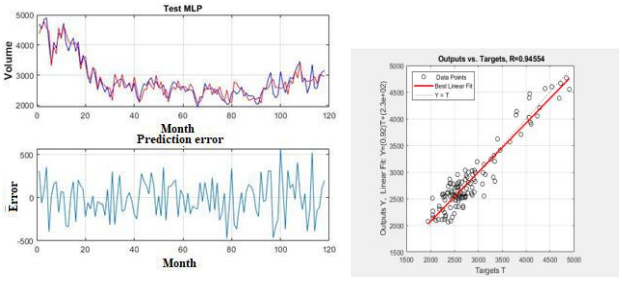

Fig. 3: Comparison and prediction error of kerosene consumption prediction model.

6.2 SUPER FUEL CONSUMPTION PREDICTION MODEL

For super fuel consumption prediction model, the parameters values producing the lowest error values are shown in Table 2. Comparison and prediction error results are shown in Fig. 4.

Table 2: Parameter values for super fuel consumption prediction model

ANN – Super fuel consumption prediction model
Learning epoch: 5000
Optimization algorithm: SCG
CPU Time Training: 47 seconds
No. inputs 12
No. hidden units 10
Error function Sum of squares
RMSE 412.0136
MAPE 2.8587
R 0.972144922528029 (97%)

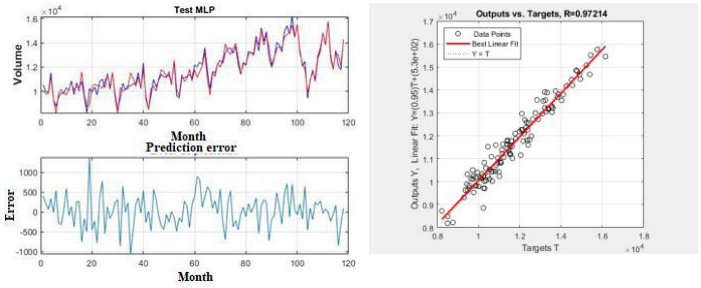

Fig. 4: Comparison and prediction error of super fuel consumption prediction model.

6.3 GAS OIL CONSUMPTION PREDICTION MODEL

For gas oil consumption prediction model, the parameters values producing the lowest error values are shown in Table 2. Comparison and prediction error results are shown in Fig. 5.

Table 3: Parameter values for gas oil consumption prediction model

ANN – Gas oil consumption prediction model
Learning epoch: 5000
Optimization algorithm: SCG
CPU Time Training: 56 seconds
No. inputs 12
No. hidden units 15
Error function Sum of squares
RMSE 1062.2700
MAPE 1.7881

R 0.981267067972050 (98%)

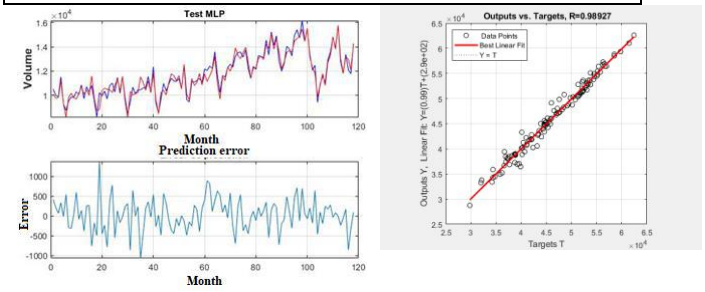

Fig. 5: Comparison and prediction error of gas oil consumption prediction model

6.4 MODEL ASSESSMENT

After performing simulations for each model, output performance gives satisfactory result with more than 95% confidence range to predict energy consumption up to 18 months. In model assessment, prediction especially for super fuel consumption from June 2019 to May 2021 is shown in Fig. 6. According to the study, the accuracy this prediction result reaches more than 97%.

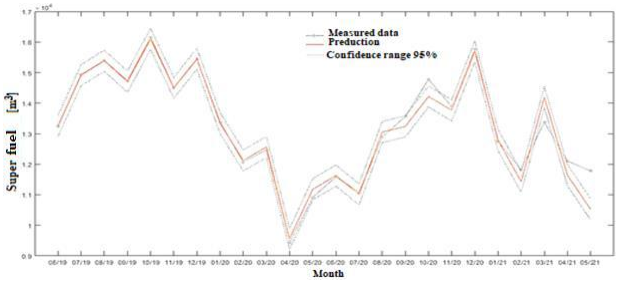

Fig. 6: Data comparison for super fuel consumption forecast

VII. CONCLUSION

Univariate neural network models were used to estimate kerosene, super fuel and gas oil consumptions in Antananarivo region. Each model has run in three stages such as training, testing and evaluation stages. Neural network parameters values and hidden nodes number are chosen with respect to the minimum RMSE. Backpropagation algorithm performed as learning algorithm. This algorithm adjusts efficiently the network weights. Well-trained models using data energy consumption in Antananarivo during the period from January 1995 to June 2021 exhibit satisfactory result. In fact, models are able to estimate kerosene, super fuel and gas oil consumptions in Antananarivo with 95%, 97% and 98% accuracies, respectively.

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