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NEURO-FUZZY STRATEGIES FOR PREDICTION AND MANAGEMENT OF HYBRID PV-PEMFC BATTERIES SYSTEMS

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ABSTRACT
The development of hybrid renewable energy systems and the resulting non-linear behavior has led to the rise of artificial intelligence techniques to deal with modelling, prediction, management and control of energy conversion from various sources in the systems. In this paper, an adaptive neuro-fuzzy inference system (ANFIS) for the management and control of the energy flow of a hybrid photovoltaic-fuel cells-battery system is implemented. The ANFIS structure obtained was compared to an artificial neural network (ANN). The results show that ANN provided good prediction in the management of the energy flow of the hybrid system but better results were obtained with ANFIS.
***Keywords*:** Photovoltaic, fuel cell, batteries, energy management, artificial neural network, adaptive neuro–fuzzy interference.

1. INTRODUCTION

Due to increased world electric energy demand, the difficulty of access to the electricity grid for remote communities, the impact of oxygen dioxide (CO_2) and other greenhouse gases produced by coal-based conventional electric energy production techniques on the environment, researchers have developed new techniques of production of electricity, commonly called renewable energies, to solve problems caused by conventional techniques (El-Sharkh et al., 2004; Rekioua et al., 2014; El-Shatter et al. 2002; Silva et al., 2013). These techniques convert natural forms of energy such as solar irradiance, kinetic wind energy, etc. into electric energy that can be stored in batteries, super-capacitors or hydrogen tanks through the conversion of electrical energy into hydrogen via electrolysers.

Considering these renewable sources, solar energy has the greatest potential due to its availability. It is free to harvest and can be transformed directly into electric energy by photovoltaic generators. However, changes or variations of solar irradiation, ambient temperature, and load, cause instability to the photovoltaic generator output with a negative impact on users. To overcome this situation, other renewable energy systems and storage units can be integrated with PV generators to form a hybrid system. Considering the hybrid systems that have been developed so far, the most popular is the photovoltaic-proton exchange membrane fuel cells-batteries. This system uses the PV generator as the primary energy source, while fuel cells and batteries are used as auxiliary or backup sources (Mutombo et al., 2017).

There is a conflictual of interest in maintaining the state of charge (SOC) of the battery in a certain range to improve its lifetime on the one hand and optimization of hydrogen consumption on the other hand. Therefore, energy management and control between different sources is necessary.

In this work, an intelligent energy flow control based on an adaptive neuro-fuzzy interference system (ANFIS) is developed to ensure energy management between different sources and loads for a better load supply and optimum operation of a hybrid-photovoltaic fuel cell-battery system.

2. REVIEW OF ARTIFICIAL INTELLIGENCE APPLIED TO PHOTOVOLTAICS AND FUEL CELLS SYSTEMS

The use of artificial intelligence techniques in the field of engineering has opened a new window on the control of non-linear systems and the optimization of calculations. The most popular of those techniques are fuzzy logic (FL) and artificial neural networks (ANN).

FL and ANNs have been applied to PV systems for modelling, simulation and control as well for the prediction and control of maximum power point tracking (MPPT) (Mellit & Kalogirou, 2008; Mellit et al., 2009). Ohsawa et al. (1993) applied an ANN for the operation and control of PV-diesel systems. Moreno et al. (2000) proposed an algorithm based on an FL to control a stand-alone PV system. A new parameter called weighted loss of load probability (WLLP), which is a weighted sum loss of load probability of individual loads, was introduced. The comparison of the performance results provided by the fuzzy controller system compared to the linear control strategy for load handling based on a user's priority assignment to individual loads within the PV system showed a significant proficiency of WLLP. Mellit et al. (2004) used an FL controller to control the MPPT of a stand-alone PV system. Patcharaprakiti et al. (2005) proposed an MPPT method using an adaptive fuzzy logic controller for grid-connected PV systems. Bahgat et al. (2004) used a neural network to estimate the maximum power and the operating power of a PV module. The proposed neural network detects with accuracy the power produced in the case of a direct coupling or maximum power output. The accuracy of the neural network is the same for all the operating conditions. Abd El-Shafy et al. (2003) used fuzzy logic to evaluate the proper performance of the MPPT controller of a stand-alone PV system. The results obtained were compared to a proportional-integral (PI) controller. Based on the author's findings, experimental results show that the system implemented with the fuzzy logic controller or PI controller provides a good operating power of the PV array when compared to the direct coupling of the PV.

Teken et al. (2007) propose a management strategy for embedded fuel cells based on fuzzy logic controllers. Hatti (2007) developed a neural network based on a PI controller used for neural network system training. Bhoopal et al. (2009) investigated the performance and the prediction for a PEMFC system using the backpropagation (BP) network. By using the fuel cells stack current and hydrogen pressure as model input, he succeeded in the prediction of PEMFC voltage and current. In the same way, Rakhtala et al. (2009) proposed a neural network model to control the stack terminal voltage and improve the system performance by using air pressure as the control signal. Simulation results proved that the applied feed-forward neural network control can track the fuel cells terminals' voltage and improve the system's overall performance. Other intelligent techniques like genetic algorithms have been also used, more details can be found in Mellit and Kalogirou (2008), and Mellit et al. (2009).

Two or more artificial intelligence techniques can be combined to use the advantages of one or many techniques to overcome the weaknesses of one another and vice versa to produce a hybrid intelligent system. Each of those techniques is chosen and used based on the type of data to be processed or the type of problem to be solved.

Until 2008 few applications of neuro-fuzzy systems for PV modelling had been developed. The first model was proposed by Mellit and Kalogirou (2008) in which the authors used a neuro-fuzzy system to model and simulate stand-alone PV systems. For PV systems modelling, it is recommended to find suitable ANFIS models for different components of the system in variable climate conditions. The overall block diagram of the developed global model is given in Figure 1.

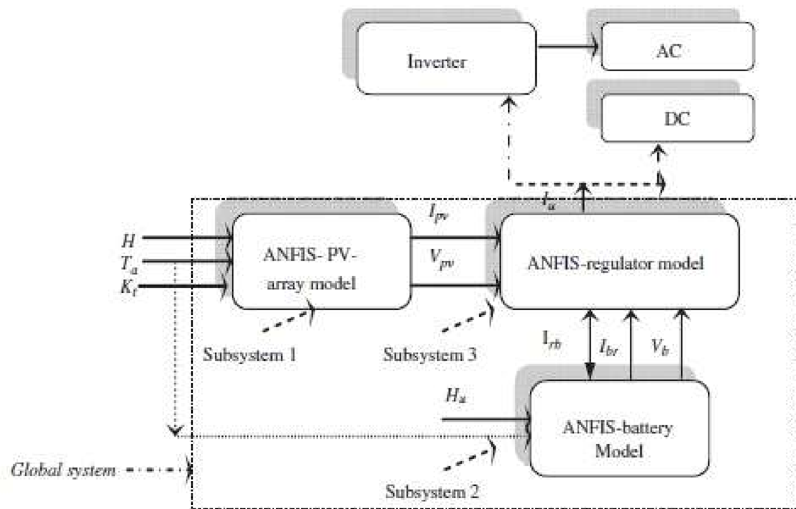


Figure 1. Block diagram of developed global model (Mellit et al, 2009).

The correlation coefficient between measured values and values estimated by the ANFIS give a good prediction with a precision of 98 %. The second application was proposed by Abdulhadi et al. (2004) in which the authors described a recently installed hybrid modeling technique computer program that facilitated PV cell modeling with previously measured data for different given operating conditions. The technique used neuro-fuzzy models to predict the short circuit current and the open circuit voltage of the PV cell, followed by the coordinated translation of the current-voltage measured response.

3. DESCRIPTION AND OPERATION OF THE SYSTEM

For better performance, different renewable energy sources and storage systems can be combined into one hybrid system for the production of electric energy, each source as a sub-system compensating for the weaknesses of the others. Advantages and weaknesses of principals energy sources can be found in Laura (2004), Rahman and Tam (1988), Tam and Rahman (1988), Wei et al. (2007), Mcgowan and Manwell (1999), Belhamel et al. (2002), and El Khadimi et al. (2004).

This study is based on a hybrid PV proton exchange membrane fuel cell (PEMFC) system comprising a photovoltaic array of 24 Q-PEAK 250 monocrystalline solar modules with fixed orientation collectors for a direct current standard test condition (DC STC) rated power of 6 000 W able to provide about 8 500 kWh/year, more than the average of 8 300 kWh/year needed for Durban modest household electricity demand. Details about the design and size of the PV generator can be found in Mutombo (2012). To overcome the variance of the PV array generator output under different insolation levels, a 2000 Horizon PEMFC was coupled to the PV array generator. This fuel cell was used with an electrolyser to produce hydrogen from water using electrical energy from the PV array generator.

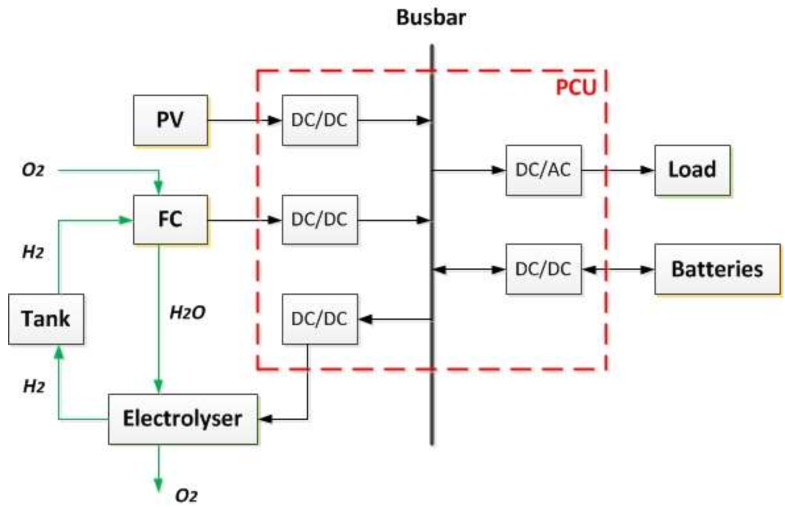


Figure 2. Hybrid PV PEMFC Topology (Mutombo et al., 2017).

The lithium-ion battery bank comprised four batteries connected in series and connected to the system to compensate for the poor dynamic response of fuel cells to transient power demand. This type of battery has a high energy density, a long life cycle and a relatively low self-discharge rate. All the sub-systems and the load were connected to the busbar through different power electronic interfaces, together constituting the power conditioning for the hybrid system. Details about system components and their functions are given in Mutombo et al. (2017) and Mutombo (2012). The schematic diagram is given in Figure 2.

In this hybrid system, the photovoltaic generator supplied the load with electric energy as the main energy source, the PEMFC stack and battery bank operated as an auxiliary energy source and supplied the load in case of low solar irradiance or failure of the PV generator to supply the energy need to the load. A large amount of energy demand was supplied by the PV generator primarily and then by the fuel cells secondarily followed by the battery bank.

4. CONTROL STRATEGIES

The main challenge met by combining different energy sources in an integrated system is the control of the energy flow from different sub-systems to meet the load demand. This is difficult to accomplish using classic control tools due to the variable nature of the output energy from sources like photovoltaic systems, but also the variable nature of the connected load leading to the non-linear model of the system. Classic control methods produce good results for linear systems.

System control is recommended to assure an efficient and robust power transfer from different sources to the load without damaging the components. In order to assure a continuous power supply to the load, the controller manages the energy supply to the load by regulating the DC bus and balancing the energy flow from all sources to satisfy the connected load demand and other constraints.

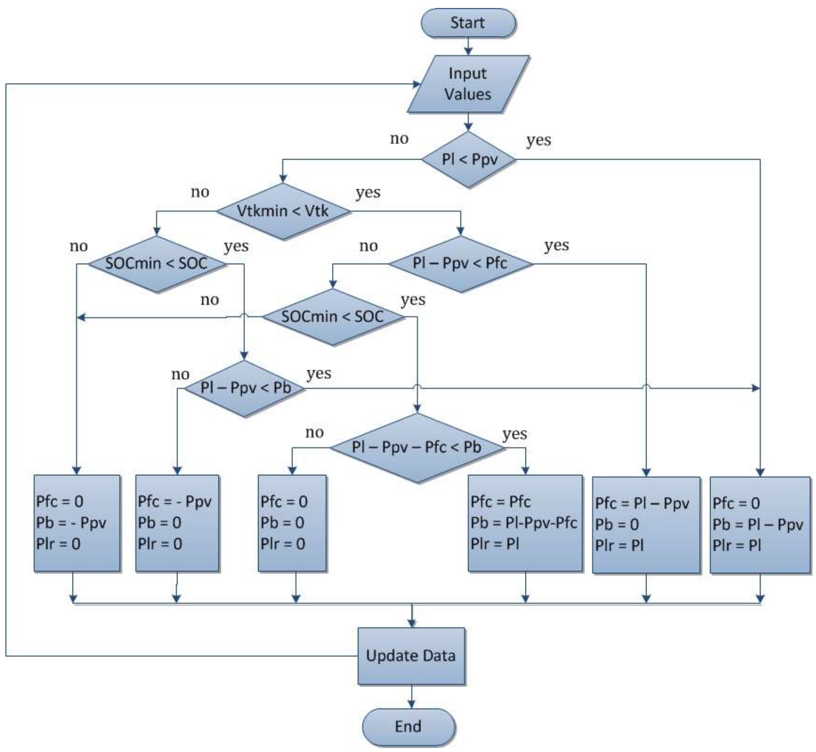


Figure 3. Flow chart Energy Management (Mutombo et al., 2017).

Different control strategies can be used to reach the energy management goal. Some of those can be in conflict with others as we can expect. This way, balance and compromise are necessary. For example, it may be anticipated to reach a maximum utilisation of fuel cells as a secondary energy source and minimise battery use to improve battery life or vice versa to consume low hydrogen. The proposed control strategy on the energy flow chart nature developed in Mutombo et al. (2017) was primarily to increase battery life and then provide low or optimum hydrogen consumption, assuring a continuous supply of electric energy to the load based on the overall system capability. The flowchart for control and energy flow management is given in Figure 3.

Due to the nature of the data set used, only ANN and ANFIS were used for the energy management and control in this work and the simulation results obtained from these two techniques were compared to the expected values.

5. ARTIFICIAL NEURAL NETWORKS

5.1 ANN algorithm and structure

ANN models are computer programs designed to imitate human ways of treating information in order to predict, classify and control (Al-Alawi et al., 2007). ANN is widely recognized as a technology offering an alternative way to solve complex problems. The ANN's ability to learn spontaneously from examples, "reason" from imprecise data sets and produce adequate and accurate results from new information that had not been stored in the memory has increased the application of this technology in many engineering fields with great success (Al-Alawi et al., 2007). ANN models operate like a black box, with no need for detailed system information to obtain results. The major construction block for any ANN architecture are the processing elements called neurons. Neurons are located in one of the following three layers: the input layer, the hidden layer and the output layer. Input neurons receive data from the external environment, hidden neurons receive signals from all other neurons from the previous layer and the output neurons return the information to the environment. Those neurons are connected together by communication links in network topology (Al-Alawi, 2004). This topology has an important effect on the operation and performance of the network.

An ANN determines the relationship between input variables and outputs by learning previously recorded data. After being trained, the ANN can be used to approximate an arbitrary map of input-output data sets (Veerachary et al., 2003). Among training algorithms available, the back propagation algorithm (Veerachary et al., 2002; Wichert & Lawrance, 2000) is one of the most widely used because it is stable, robust and easy to implement. In back propagation architecture, each element or neuron receives input from the external environment (real world) or from other neurons, process that input, and produce a specific output. The back propagation uses the supervised training technique. In this technique the weight of connections between layers and threshold processing elements are firstly initialised to the values of small random numbers. The network is then presented with a set of training patterns, with each pattern consisting of an example of the problem to be solved (the input) and the desired solution to the problem (the output). Those training patterns are presented several times to the ANN model and an adjustment is performed after each iteration whenever the network output is different from the desired output value. This process continues until the weights converge to the new desired error or the output reaches a satisfactory point (Al-Alawi et al. 2007). To be sure of the network precision and its capability of generalisation, the network must be tested on a continuous basis and must be followed during training and testing operations. To be sure that the ANN model provides a correct prediction or classification, predicted results produced by the ANN models can be validated or compared against expert predictions for the same case or they can be validated against results from another computer program.

5.2 Simulation and validation of an ANN model

Based on the nature of the problem being time series prediction, dynamic time series neural networks were used. Before the simulation, the first step was to define the problem by selecting a data set. Then the network was trained to fit that time series data set using nonlinear input-output prediction with the number of hidden neurons of 5 and the number of delays of 2. Many algorithms exist for this purpose, such as Levenberg-Marquardt, Bayesian regularisation, scaled conjugate gradient, Jacobien calculations, etc for the training of the network. The field of application of each algorithm is determined by its advantages and inconveniences (Matlab, 2014).

A total of 720 target timesteps were selected for validation and testing. 70 % of the data was allocated to train the network, 15 % for validation and 15 % for testing. During the training process, data were presented to the network and the network was adjusted according to its error. To validate the network, 15 % of the data allocated to validation was used to measure the network generalization and to stop the training process when generalization was reached. The network performance during and after training was measured by using the remaining 15 % set of data, which has nothing to do with training.

A Levenberg-Marquardt algorithm was used for training the network. In this algorithm, the training stops when generalization stops improving. This can be seen in Figure 4 by an increase in the mean square error (mse) which is the average square difference between outputs and targets for the validation samples. The best validation performance was obtained at epoch 22, after training the network multiple times to improve its performance.

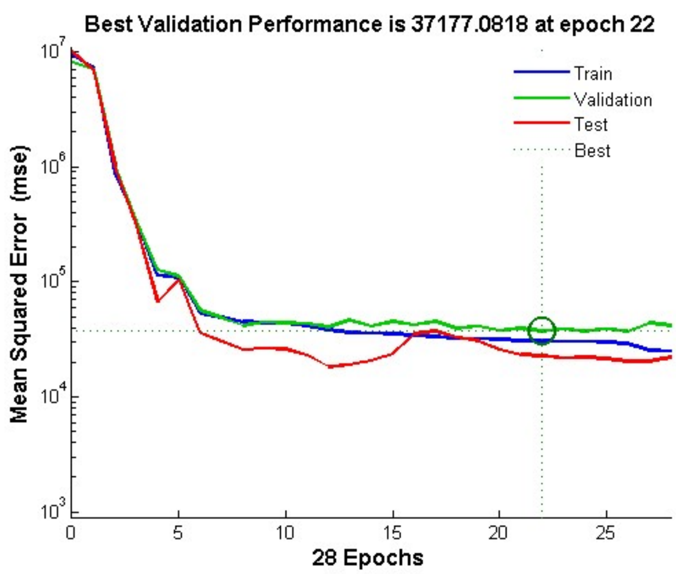


Figure 4. ANN Performance

This network provides good results as can be seen in Figure 5 and Figure 6 related to the correlations.

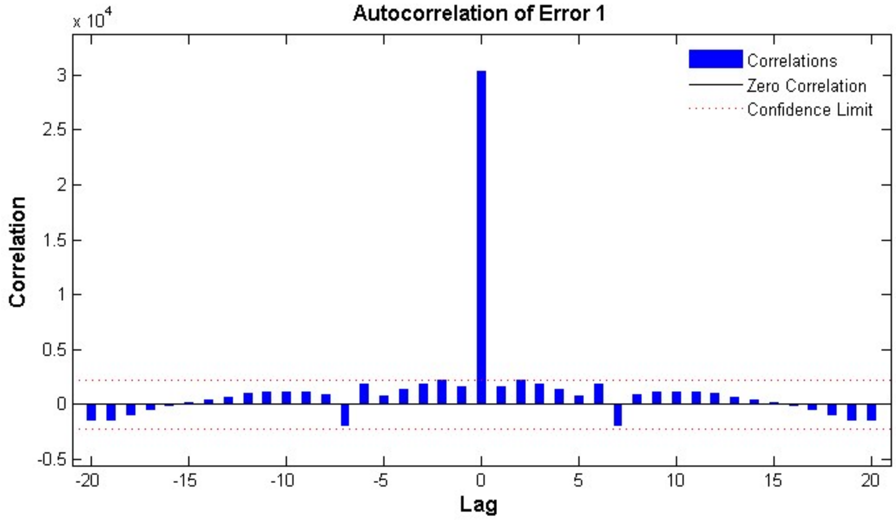


Figure 5. ANN error autocorrelation.

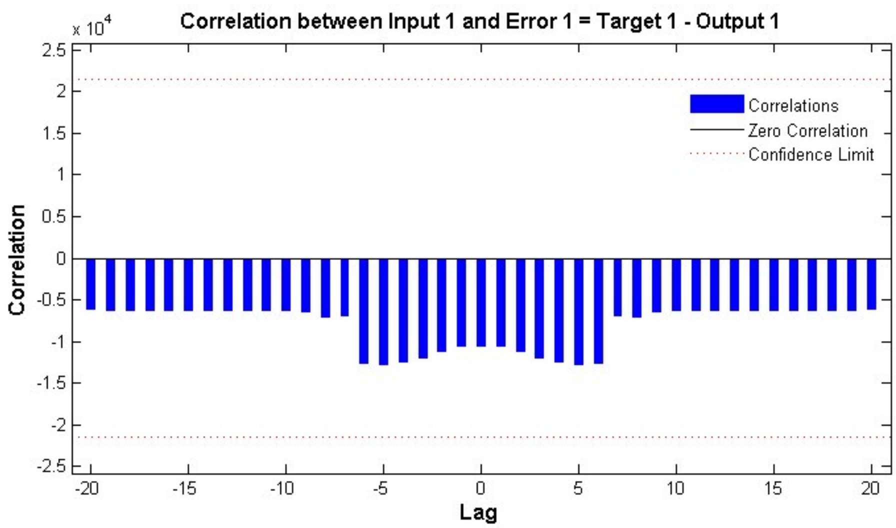


Figure 6. ANN input-error cross-correlation.

For a perfect prediction model, there should only be one nonzero value of the autocorrelation function, and it should occur at zero lag which corresponds to the mean square error. The present model presented a significant correlation in the prediction errors. It can be noticed that for this case, after multiple pieces of training, all of the correlations fell within the confidence bounds around zero making the model good to manage the energy flow of the hybrid system. The time-series response of the model and error is given in Figure 7.

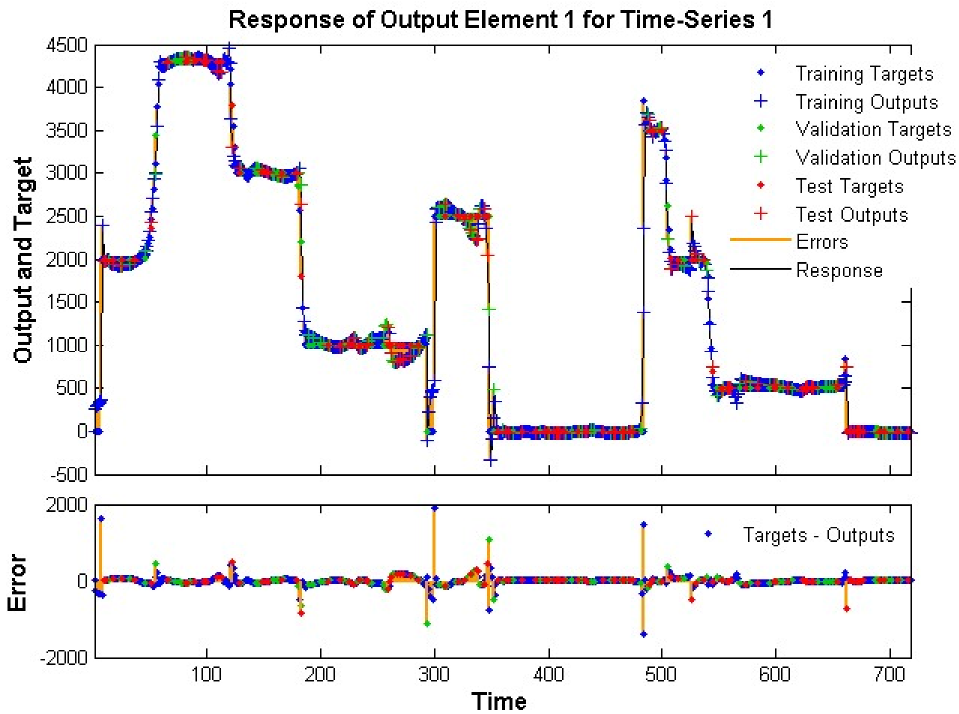


Figure 7. ANN time-series response.

The correlation between outputs and targets is measured by the regression R values and is given in Figure 8. The value of 99 % is obtained for the regression, confirming the accuracy of the network to manage the energy flow of different components of the PV- PEMFC- battery system and the load.

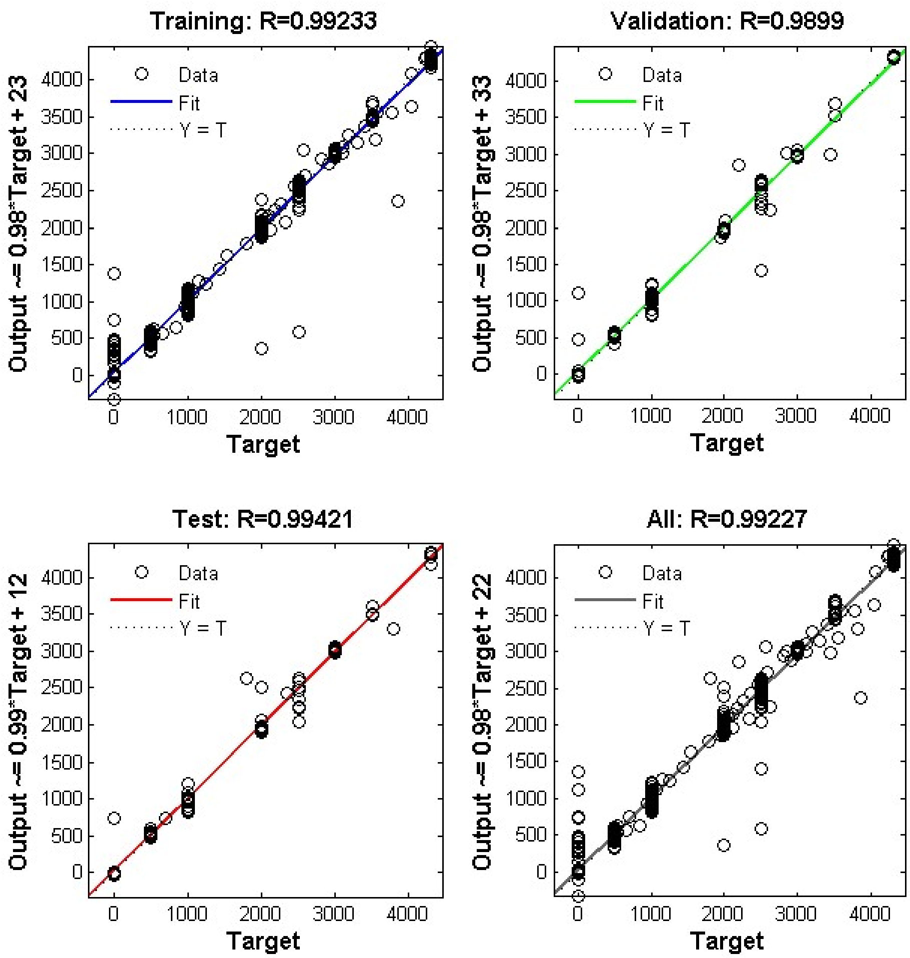


Figure 8. ANN regression.

Figure 9 shows the structure of the network.

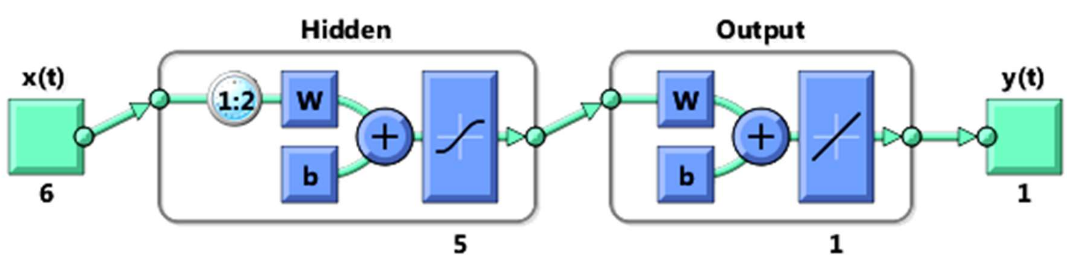


Figure 9. ANN structure.

This network was constituted by 6 inputs related to the load, the PV power, the FC power, the battery power, the tank hydrogen volume and the battery state of charge (SOC) respectively, with 5 hidden layers with 2 delays and one output layer.

6. NEURO-FUZZY CONTROL STRATEGIES

6.1 Neuro-fuzzy algorithm and structure

Because an ANN does not consider the statistical distribution presuppositions and characteristic data, they are practically more efficient than the statistical methods often used. They use a linear approach to produce the model meaning that when dealing with nonlinear and complex data, those methods can generate a highly accurate model similar to the original or defined model from those data. The high learning ability of ANN has made this method a good choice when combined with a fuzzy system (Rezazadeh et al., 2012). The combination of the ANN with the fuzzy method generates a hybrid technique called the neuro-fuzzy technique in which each of those two systems can cover the weaknesses of the other and improve the neuro-fuzzy system efficiency (Mellit et al., 2009). A neuro-fuzzy system uses the learning method derived from the ANN to find the fuzzy system parameters that are appropriate membership functions and fuzzy rules. Based on the fact that the fuzzy systems are universal approximators, it can be expected that their equivalent neural network representations will have the same propriety. As mentioned before, the reason to represent a fuzzy system in terms of a neural network is to use the learning capability of a neural network to improve performance like the fuzzy system adaptation.

ANN is a calculation tool used to test data and generate models from those data. Based on the researcher's objectives, different types of ANN can be used. One of the most well-known is the multilayer feed-forward neural network that uses a neural network (NN) to be instructed by a supervisor. This NN is used to solve problems related to the study of input-output sets of relationships. In reality, it is a method to instruct by the supervisor to determine the relationship between data by training a series of data sets. In the error backpropagation algorithm, the network creates an output set for the provided input criterion and compares the reaction with the proper reaction of each neuron. The weights of the network are corrected to reduce the error and the following criterion has emerged. The weights are corrected continuously until the total errors are less than the authorised values. Because this algorithm has a negative gradient of the error function, the correction of the inputs decreases the mean square error gradually (Lippmann, 1987; Tong 1997). Moreover, the neuro-fuzzy networks normally calculate node outputs up to the last layer at each period of instruction. This means that the parameters obtained are calculated by the least square error method. After error calculation and returning backward way, the error reports are distributed in parameter conditions and their values are corrected by the descending gradient method error.

From different versions developed of neuro-fuzzy methods, the ANFIS developed by Jang (1993) is the most powerful and popular. In this neuro-fuzzy system, the learning algorithm coincides with the integrated learning approach. The principal approach of the instruction in this structure is the backpropagation that scatters the error value toward inputs by the steepest descent gradient algorithm and corrects the last parameters (Jang, 1993). These structures are used in control systems and many other applications. In recent years many investigations have been conducted to apply the ANFIS system in engineering modelling processes (Rezazadeh et al., 2012).

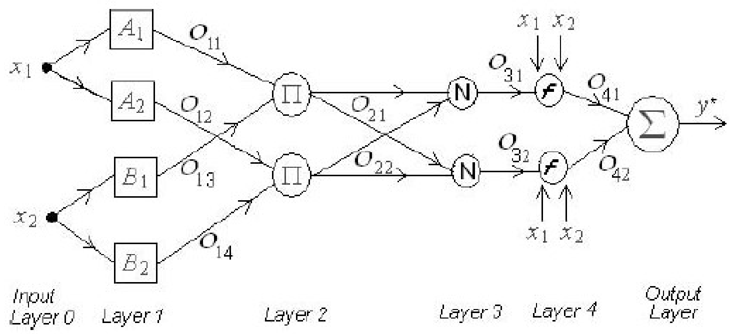


Figure 10. First-order Sugeno fuzzy model with two rules (Nguyen et al., 2003).

Like other fuzzy systems, the ANFIS structure is organised into two parts, the introductory and concluding parts being related by a series of rules. The representation of the preceding section of the neural network is just a graphic display of the computation steps in the Sugeno-Takagi process shown in Figure 10. In order to make this representation more useful to implement control laws, it is required to equip this representation with an efficient learning algorithm. In a conventional neural network, the backpropagation algorithm is used for learning or adjusting weights in the connecting arrows between input-output neurons of training samples (Nguyen et al., 2003). The ANFIS uses backpropagation or a combination of least squares estimation and backpropagation for membership function parameter estimation (Matlab, 2014). In order to train a fuzzy-neural network, a series of training data in the form of inputs-outputs is needed, as a specification of rules, as well as a preliminary definition of correspondent membership functions (Matlab, 2014).

6.2 Simulation and validation of the ANFIS model

A data set of 720 x 7 array was used for training an ANFIS and a 360 x 7 array for checking. The first 6 columns represented the input of the ANFIS model and the last colon was related to the output. The fuzzy interference system (FIS) was generated by using a grid partition assigning 2 membership functions to each input and using the generalized bell-shaped membership function (gbellmf) type for the inputs and a linear membership function for the outputs.

The initial FIS model was generated by applying the grid partition technique which generates a single-output Sugeno-type FIS by using grid partitioning on the data set ANFIS properties, as shown in Figure 11.

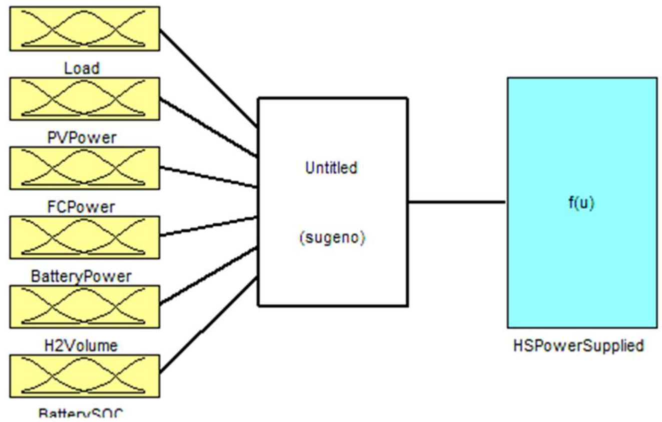


Figure 11. ANFIS properties.

ANFIS membership functions are shown in Figure 12.

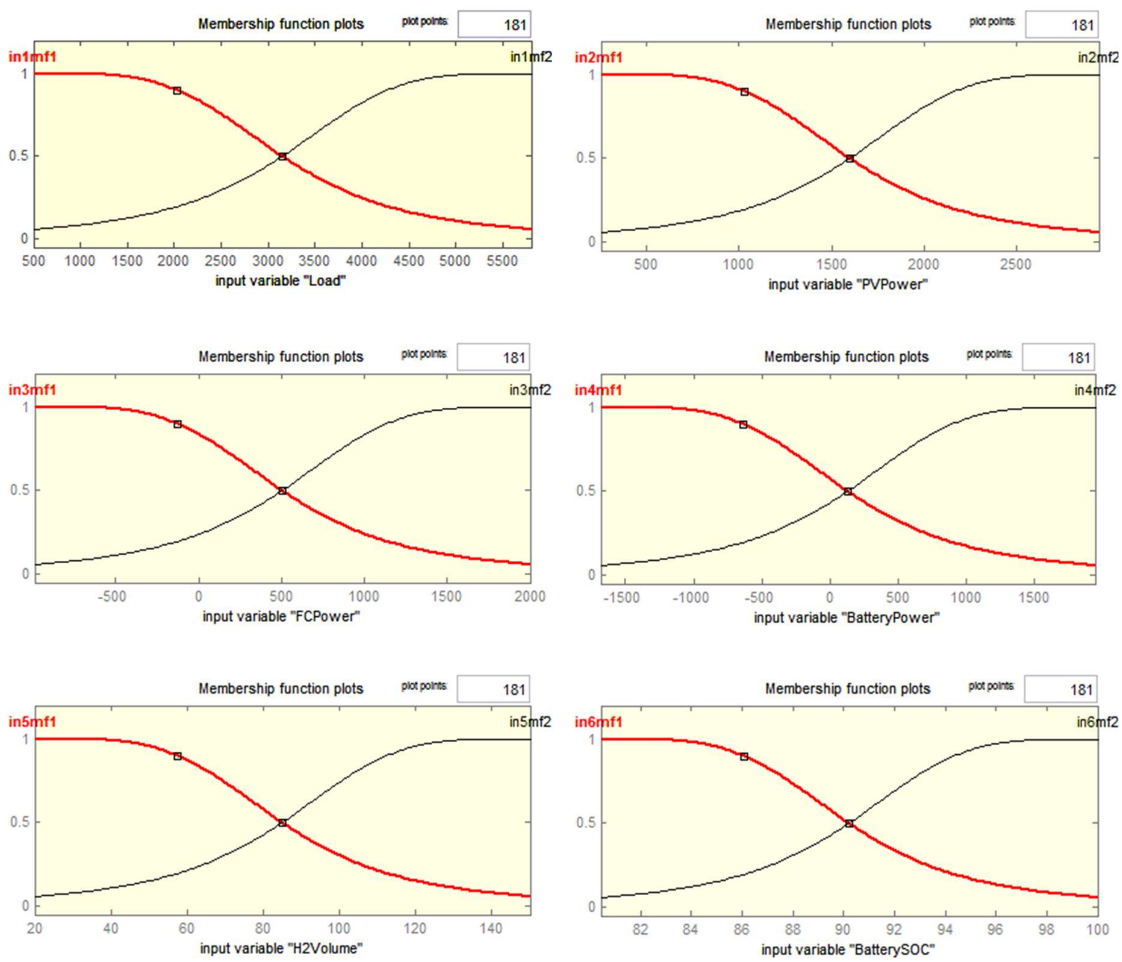


Figure 12. ANFIS membership functions.

The FIS was trained using the hybrid optimization method which is a combination of the least-squares and backpropagation gradient descent methods with an error tolerance of 0.01

and 50 epochs. This trained the fuzzy system by adjusting membership function parameters that best model this data by emulating the training data. The training error obtained is shown in Figure 13.

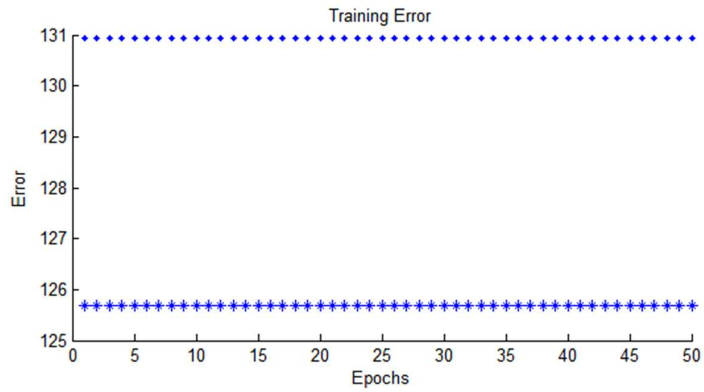


Figure 13. ANFIS training error.

It is evident that the checking error of 130.941 was higher than the training error of 125.678. The ANFIS training was completed at epoch 2 with an error of 155.661. The time-series response of training data and checking data are shown in Figure 14 and Figure 15 respectively.

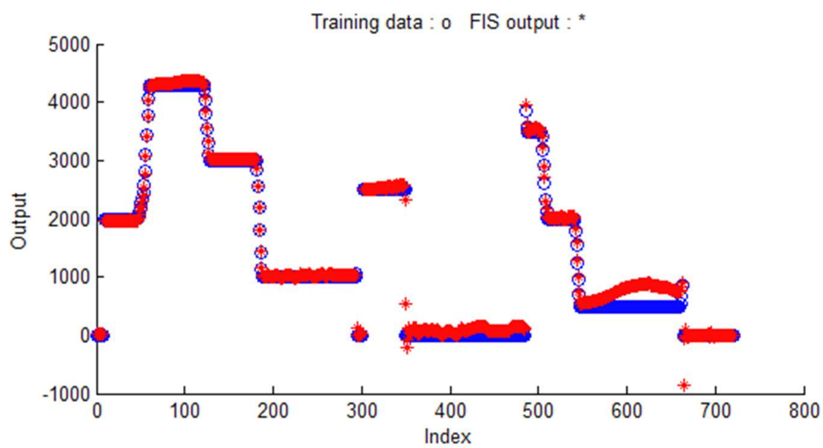


Figure 14. ANFIS training data time-series.

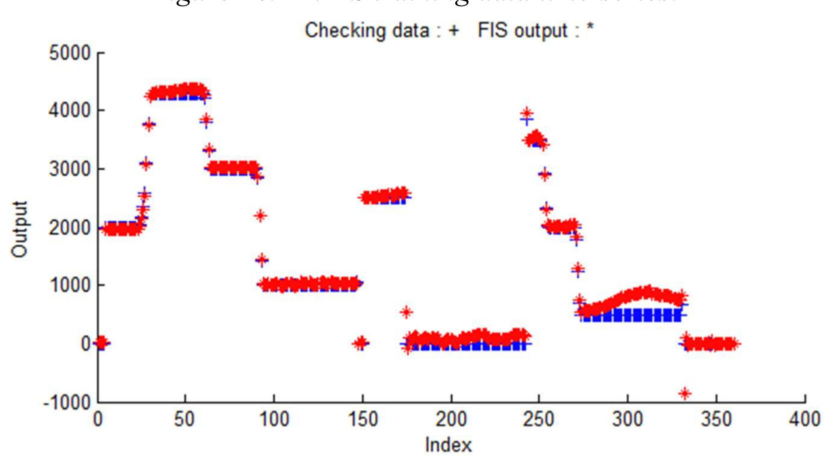


Figure 15. ANFIS checking data time-series.

It can be seen that the time series obtained using ANFIS for the training data and the checking data are the same with differences in indexes that are related to the number of data sets used (Matlab, 2014).

The ANFIS information is given in Table 1.

Table 1. ANFIS information.

PARAMETERS	VALUES
Number of nodes	161
Number of linear parameters	448
Total number of parameters	484
Number of training data pairs	720
Number of checking data pairs	360
Number of fuzzy rules	64

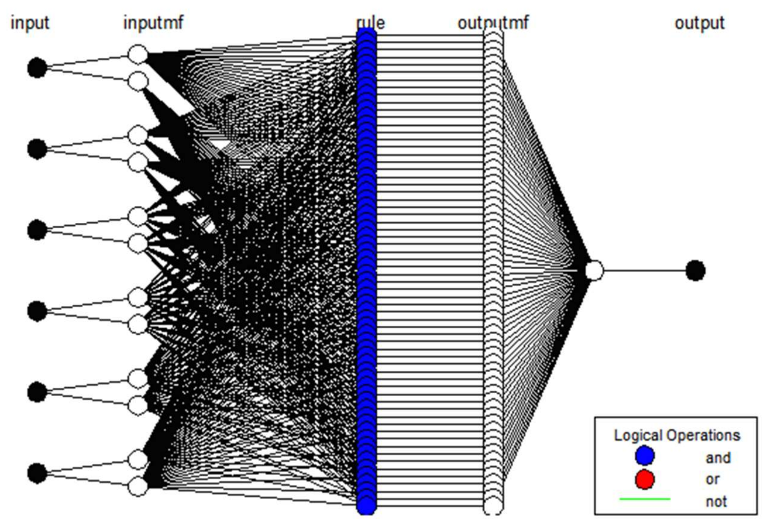
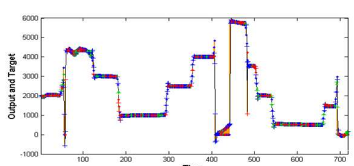
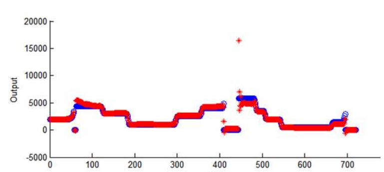
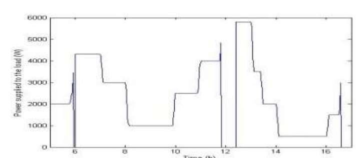


Figure 16. ANFIS structure.



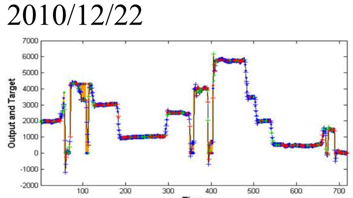


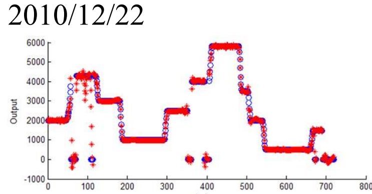


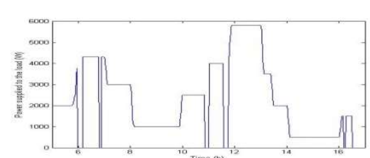
ANN Time-series response for summer day of 2010/12/22

ANFIS Time-series response for summer day of 2010/12/22

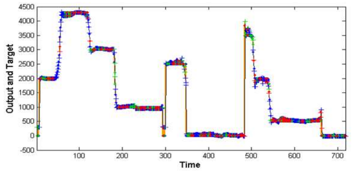
PV-FC batteries response for summer day of 2010/12/22

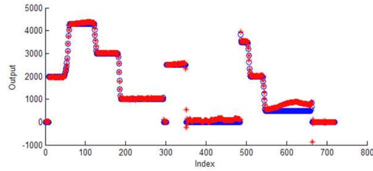


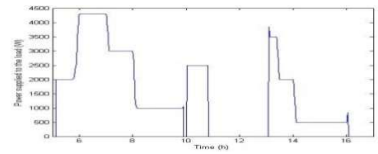




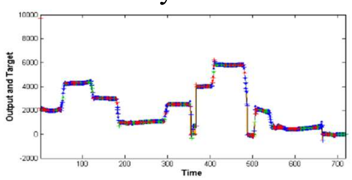
ANN Time-series response for summer day of 2010/12/29	ANFIS Time-series response for summer day of 2010/12/29	PV-FC batteries response for summer day of 2010/12/29

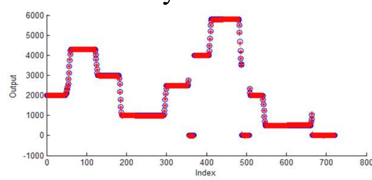


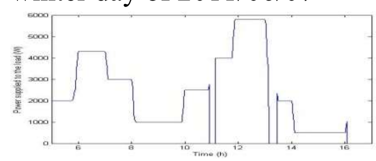




ANN Time-series response for winter day of 2011/06/07	ANFIS Time-series response for winter day of 2011/06/07	PV-FC batteries response for winter day of 2011/06/07







ANN Time-series response for winter day of 2011/06/28	ANFIS Time-series response for winter day of 2011/06/28	PV-FC batteries response for winter day of 2011/06/28

Figure 17. Time-series response of ANN and ANFIS for different weather conditions.

The structure given in Figure 16 represents the ANFIS structure of the model. The structure contains 64 fuzzy rules and 484 parameters. We can recognize three different layers in the ANFIS network structure that make it a multilayer network. This type of network, which is a SUGENO-type fuzzy system with six inputs and one output, is shown in Figure 16.

In short, the first layer in the ANFIS performs the fuzzy formation and the second layer performs the fuzzy rules. The third layer performs the membership function normalisation, and the last layer calculates the network output. From this, it is evident that the first layer in the ANFIS structure is an adaptive layer.

7. COMPARISON OF THE ANN MODEL AND ANFIS MODEL

With new data set load to ANN, and ANFIS structures obtained, time-series responses in Figure 17 were obtained for different days. The rmse values of ANN and ANFIS networks are given in Table 2.

Table 2. The rmse values of ANN and ANFIS networks.

DAYS	ANN RMSE	ANFIS RMSE
Summer day of 2010/12/22	152.60	147.16
Summer day of 2010/12/29	225.25	181.55
Winter day of 2011/06/07	192.81	120.18
Winter day of 2011/06/28	157.35	12.33

From Table 2 it can be seen that the values of ANFIS are small compared to the ANN values but the differences between the two are not substantial, both networks give good results. Furthermore, it can be seen that the ANFIS results were obtained at epoch 2 while the ANN results are obtained after epoch 15 after much more training of the network. This means that the ANFIS network is better and faster compared to ANN for the prediction and management of hybrid PV-PEMFC-battery systems.

8. CONCLUSION

ANN and ANFIS networks were developed for the prediction and energy management of a PV-PEMFC-battery system. The two systems were simulated and analysis was undertaken for four different weather conditions for the same variable load. The simulation results showed that both systems give good results for a typical non-linear system which cannot be easily modelled by the use of classic control techniques. However, it was observed that the ANFIS provided better results than the ANN by combining both ANN and fuzzy-logic technique features.

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