



Hybrid energy system evaluation in water supply system energy production: neural network approach

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Abstract

Water supply systems are large consumers of energy and the use of hybrid systems for green energy production is this new proposal. This work presents a computational model based on neural networks to determine the best configuration of a hybrid system to generate energy in water supply systems. In this study the energy sources to make this hybrid system can be the national power grid, micro-hydro and wind turbines. The artificial neural network is composed of six layers, trained to use data generated by a model of hybrid configuration and an economic simulator – CES. The reason for the development of an advanced model of forecasting based on neural networks is to allow rapid simulation and proper interaction with hydraulic and power model simulator – HPS. The results show that this computational model is useful as advanced decision support system in the design of configurations of hybrid power systems applied to water supply systems, improving the solutions in the development of its global energy efficiency.

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1. Introduction

In the last decades, the managers of such water supply systems have been concerned with the reduction of energy consumption as well as with the strong influences of climate changes on water patterns. The recent increase in oil prices has made the search for alternatives to generate energy using renewable sources, becoming renewable energy systems as valuable energy sources, in particular through the use of hybrid energy solutions. Hybrid energy solutions for power generation are feasible applications for water supply systems that need to decrease their costs with the electrical component. These solutions take the advantage of power production based on its own available hydraulic energy as well as on local available renewable sources, saving on the purchase of energy produced by fossil sources contributing for the reduction of CO₂ emissions.

Absolute sustainability of electricity supply is a simple concept: no depletion of world resources and no ongoing accumulation of residues. Relative sustainability is a useful and more realistic concept in comparing the sustainability of two or more generation technologies. Therefore, only renewable are absolutely sustainable and presently even nuclear is seen as more sustainable than fossil. However, any

discussion about sustainability must not neglect the ability or otherwise the new technologies to support satisfactory the operation of the electricity supply infrastructure [1].

The concern with the consumption of energy in water supply systems is increasingly inducing the managers of these systems in seeking optimal solutions for the improvement of energy efficiency of such systems. The use of renewable energy is increasing, driven by the growing concern about the effect of global warming and the excessive consumption of fossil fuels, but still far from desired levels. The application of hybrid solutions based on renewable energy sources is an ideal solution for reducing the dependence on fossil fuels. The best hybrid solution to be adopted, taking the energy efficiency as the main goal, is a complex and arduous task, besides requiring multi-criterion optimization models, where the development of additional tools can become difficult.

This work aims to present a neural artificial network that capture the domain knowledge in a far more efficient way, simulating an optimization model to obtain the best hybrid system configuration for a typical water supply system.

2. State of the art review

2.1 Basic concepts

Unlike a conventional power generation system, a hybrid system by definition is one, which uses an alternative arrangement of technologies to achieve similar objectives i.e. a constant and reliable source of power. Renewable energy takes on many varying forms, each with associated strengths and weaknesses, depending on the local and type, but when combined could configure an integrated solution to achieve the energy efficiency improvement. The need for a constant reliable source of energy is fundamental, as well as the amount required [2].

The needs for water consumption, environmental targets and saving energy have become the main concerns over the last years growing to be more and more important in a near future. To achieve that, energy for pumping to deliver water to populations is needed, representing the main cost for water companies [3].

As well known renewable are generally weather dependent and their likely output can be predicted but not controlled. An alternative for the reduction of energy, is the decreasing of costs and the lesser dependence of weather factors by using complementary energy hybrid production on water supply systems, not only based on national energy grid, but also on wind generation, photovoltaic, biomass, micro hydro, among others sources.

Renewable energy creates multiple public benefits such as environmental improvement (reduction of power plant greenhouse emissions, thermal and noise pollution), reduction of energy price volatility effects on the economy, national economic security, since fossil energy is vulnerable to political instabilities, trade disputes, embargoes and other disruptions, it increases economic productivity and through more efficient production processes [3].

Renewable energy sources represent a viable option for power generation though presenting some geographical and environmental restrictions. Through the European Union Directive 2001/77/EC the indicative target for Europe to the production from renewable sources is 22% of the electricity consumed in 2010. It is expected to achieve this objective through quotas taken by different member states [4].

2.2 Hybrid energy system

In the past decade the hybrid energy system has received much attention and it is a viable alternative solution as compared to systems based entirely on hydrocarbon fuel, given flexibility to the system and a longer life cycle [5]. Commonly the hybrid system works with the national energy grid, but during the peak hours when are the higher costs in the electricity tariff, the system could be supplied by renewable sources, such as wind turbines, photovoltaic (PV) or micro turbines integrated installed within the conveyance system to power the system for pumping or turbine the flow between reservoirs, and to sell surplus energy [6].

An example of a hybrid energy network, integrated in water supply system is drinking system composed by reservoirs and pumps that can be supplied with electricity through a hybrid system, which would take into account the water consumption pattern, the electricity tariff rate, the environmental factors and the system characteristics, overcoming the weaknesses of a particular renewable energy system at a given point with the strength of another, for instance, in a day which there is not enough luminosity to produce sufficient energy at photovoltaic system, this energy is given by wind generators or micro turbines and

on days with little wind the reverse, as well as in times of low consumption of water, the photovoltaic and wind systems would outweigh the low production of a micro turbine system.

2.3 Modelling conditions

In Gupta et al. [3] the literature review reveals that the modelling of hybrid energy systems and their application in decentralized mode are quite limited. The models currently applied, are based on one of the available resources while in the literature is found application with one or two available resources. Application of models for matching the projected energy demand with a complementary combination of sources at decentralized level is the main subject. Software models (such as HOMER, PVSYST) have been used by various researchers [3, 6-8], for design and research of alternative energy systems. The need of a model for optimizing the energy management of hybrid type systems with specific operational controls is imperative. In other hand MATLAB can be used for modelling optimization to manage the water and energy in WSS. In [3, 9] linear programming was used to develop an optimization tool to obtain the best hourly operation, according to the electricity tariff, for a pumped storage system supplied by wind energy, with water consumption and inlet discharge. Others authors use different conditions (e.g. linear and non-linear programming, Genetic Algorithms) to analyse cases of daily operation in water supply systems with complementary renewable energy sources [3].

2.4 Artificial neural networks

Artificial neural networks (ANN) have been used in water distribution systems to model the degradation of water [3, 10-12]. The research has been considered promising, providing a strong base for the development of a financial-economical model, which applied with the degradation model, is able to give an integrated approach for optimizing intervention strategies in water distribution systems. Even the limitations identified in this algorithm, their prediction performance has proven to be rather good in the short and medium term.

Another research carried out analysis of water quality using ANN model [10]. To simulate the water quality inside the reservoirs an ANN model are used in preference to physical models, since the latter tends to demand a lot of lab or field efforts when comparing with ANN, which can be combined with other optimization techniques, such as dynamic programming and initial conditions and reducing in a easy way without special costs.

As part of the POWADIMA research project, a study was developed to describe the technique used to predict the consequences of different control settings on the performance of a water distribution network system, in the context of real time analyses and near optimal control. Since the use of a complex hydraulic simulation model is somewhat quite different for real time operations, as a result of computational time consumption impose, the approach adopted has been to capture its domain knowledge in a far more efficient form by means of an ANN [13].

3. Methodology

3.1 Neural conception

The creation of an ANN must comprise the following steps: patterns definition; network implementation; identification of the learning parameters; training and network testing. The conception of a new neural network hybrid energy model which can be compared with an energy configuration model and economical simulator – CES (e.g. HOMER simulator) for limited conditions will adopt the following procedures: use CES to obtain data that may be used in training process and in a reliable neural network tests together with an hydraulic and power simulator model – HPS (e.g. EPANET simulator), alternating flow rates, diameters and pipe lengths and roughness as well as differences levels of water in tanks or reservoirs, characteristic pumping parameters per energy consumption and power evaluation per pumping and turbinning procedures. Those data has been available on Ramos [14] research that uses the HPS to hydraulically balance the water supply system, determining the hydraulic behaviour of all system including the most suitable pump and turbine power for each condition.

Before starting the creation and implementation of the neural algorithms, it is necessary the creation of a complete database for the input and output data for the training and validation of the network for each system characteristics. The input data come from HPS (e.g. pump power, available head, length, flow, diameter, mean output power, water demand pattern and power consumption of the pump and difference water levels between reservoirs) and CES (e.g. mean output power of wind/hydro generator and mean head discharge/wind velocities).

These data are implemented in CES model and are useful for the economic analysis calculation based on the NPV (Net Present Value) indicator for each hybrid system studied, thus giving the most profitable economic solution. Other economic values are used such as the prices of installed equipment, energy selling prices for the national electric grid and the limitation of the number of equipment to be used in the simulation, which would bring associated errors in the training process and in the ANN validation.

The optimization algorithms and sensitivity analysis allows to simplify the evaluation of different system configurations. Inputting technology options, component costs and resource availability, CES tests all combinations creating a list of feasible configurations sorted by net present values (NPV) or cash flows in order to use then on the ANN model as output vectors.

The values of inputs obtained from HPS simulations and the output values of NPV from CES are arranged in an auxiliary file is used to compose the ANN. With the results obtained from several simulations, it was possible to create a neural network system that transcribe in part the previous modelling process through suitable decision makers, then, guaranteeing the strength and rapidity in the whole evaluation process. A flowchart describing the procedures of design the ANN applied for energy efficiency evaluation in water supply systems is shown in Figure 1.

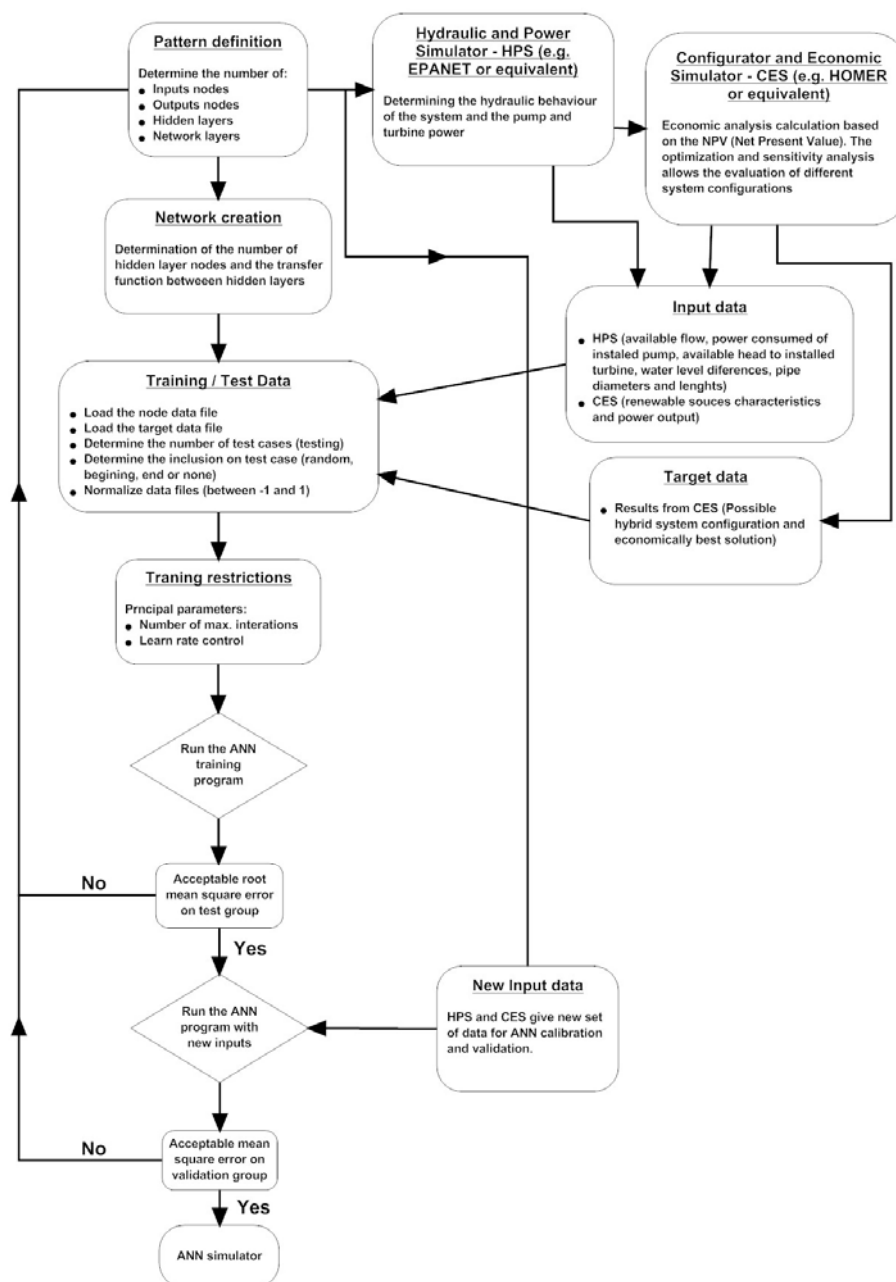


Figure 1. Flowchart of the developed artificial neuronal network

3.2 Neural network

The initially proposed method for the basic ANN to be used in this research is the MLP (Multilayer Perceptron), in which the neurons are disposed in successive layers (feed-forward). Preliminary tests are made to determine the ANN parameters that provide the best results. After the initial analysis, networks with just one layer presented very high mean square errors, and then after several attempts more than one hidden layer with various configurations of neurons are implemented.

In each neuron the following operations occur: input data endure weight application $iw\{i,m\}$ and go to an adder (additive junction), that will sum the input data, pondered by the respective synapses (iw) and receive a "bias" $b\{k\}$ coefficient that functions in a way to decrease or increase the net entrance of the activating function [15]. An activating function will be applied to restrict the amplitude of neuron output. The activating function is also referred as restrictive function once it restricts (limits) the permissible amplitude interval of the output signal to a finite value. A non-linear example of a neuron can be interpreted as the one presented in Figure 2.

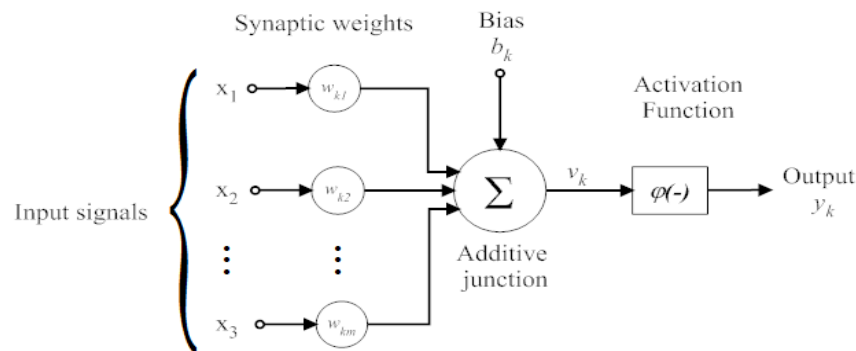


Figure 2. Non-linear example of a neuron [16]

In mathematics analyses, it is possible to describe the neuron by writing the following pair of equations:

$$u_k = \sum_{j=1}^m w_{kj} x_j \quad (1)$$

$$y_k = \varphi(u_k + b_k) \quad (2)$$

where x_1, x_2, \dots, x_m are the input signals; $w_{k1}, w_{k2}, \dots, w_{km}$ are the synaptic weights of neuron k ; u_k is the linear combiner output due to the input signals; b_k is the bias; $\varphi(\cdot)$ is the activation function; and y_k is the output signal of the neuron.

Back propagation neural networks process information in interconnecting processing elements (often termed as neurons, units or nodes) are organized into groups termed layers. There are three distinct types of layers: the input layer, the hidden layer(s) and the output layer. There are connections between the nodes of adjacent layers to relay the output signals from one layer to the next one. Fully connected networks occur when all nodes in each layer receive connections from all nodes in each preceding layer. Information enters into a network through the nodes of the input layer. The input layer nodes have the purpose to distribute the input information to the next processing layer (i.e., the first hidden layer). The hidden and output layer nodes process all incoming signals by applying factors to them (intended by weights). Each layer also has an additional element called a bias node. Bias nodes simply output a bias signal to the nodes of the current layer. All inputs to a node are weighted, combined and then processed through a transfer function that controls the strength of the signal relayed through the node's output connections.

The activation function is also referred as restrictive function or transfer function, the range of permissible amplitude of the output signal to a finite value. Typically, the range of normalized amplitude of the output of a neuron is written as the closed unit interval $[0,1]$ or alternatively $[-1,1]$, at this study the normalized amplitude adopted is $[-1,1]$ and the neural network created uses the hyperbolic tangent functions as followed presented:

$$f(Y) = \frac{(\tanh(Y) + 1)}{2} \quad (3)$$

There are 9 input neurons that correspond [i] to the length of pipe system, [ii] the water levels differences between reservoirs, [iii] diameters, [iv] the annual average power produced by the wind turbine, [v] the annual average wind velocity, [vi] flow, [vii] the head available, [viii] the annual average power produced by the micro-hydro and [x] the power consumed by the pump station.

On the output layer is used 5 neurons representing the optimization and sensitivity analysis of different system configurations corresponding to data used by CES simulator, where the neurons are represented by NPV of national electric grid configuration (NPV NG), NPV of national electric grid and wind turbine configuration (NPV NG+Wind), NPV of national electric grid and hydro configuration (NPV NG+Hydro), NPV of national electric grid, hydro and wind turbine configuration (NPV NG+Wind+Hydro) and the number of wind turbines as the best solution. In this analyses only hydro and wind sources were considered. After the input data procedure the network is trained to obtain the weights and coefficients of bias and latter validation. Many attempts of training, modifying the number of hidden calls, number of neurons and functions of transference are made until a final network, with a satisfied lesser mean square error is obtained. After this stage tests are developed with well known solutions based on CES results for the validation of the proposed neural network system. Each set of input data can be calculated in CES with different configurations of available resource (e.g. hydro, wind) depending on the site and meteorological condition, with settings labelled as in Table 1.

Table 1. Solution configurations used to obtain the best hybrid configuration

Solution configuration	Wind velocity m/s	Stream flow l/s
1	4,70	19,00
2	4,70	48,00
3	4,70	106,00
4	5,90	19,00
5	5,90	48,00
6	5,90	106,00

4. Results and discussion

In the end of training, the neural network adopted is that gives the less root mean square error (RMSE) with a good correlation. After several attempts, modifying the network topology and the number of neurons and hidden layers, the resulted network with the topology adopted was the 9 neurons for input, 40, 30, 20, and 10 neurons for the 4 hidden layers and 5 neurons for the output layer. In Figure 3 the scatter comparison of normalized targets versus net outputs shows a good approach to the optimal agreement and in Figure 4 the root mean square error of training and test settings demonstrate that at the interaction 6.00e+5 the neural network starts to become stable and use higher interactions just bring to the model more computing time, not desired at all.

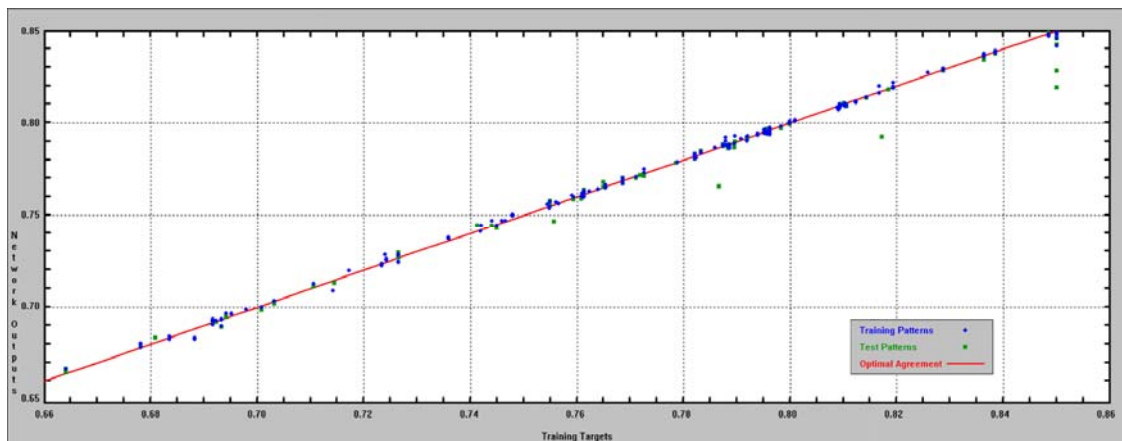


Figure 3. Scatter comparison of normalized targets set

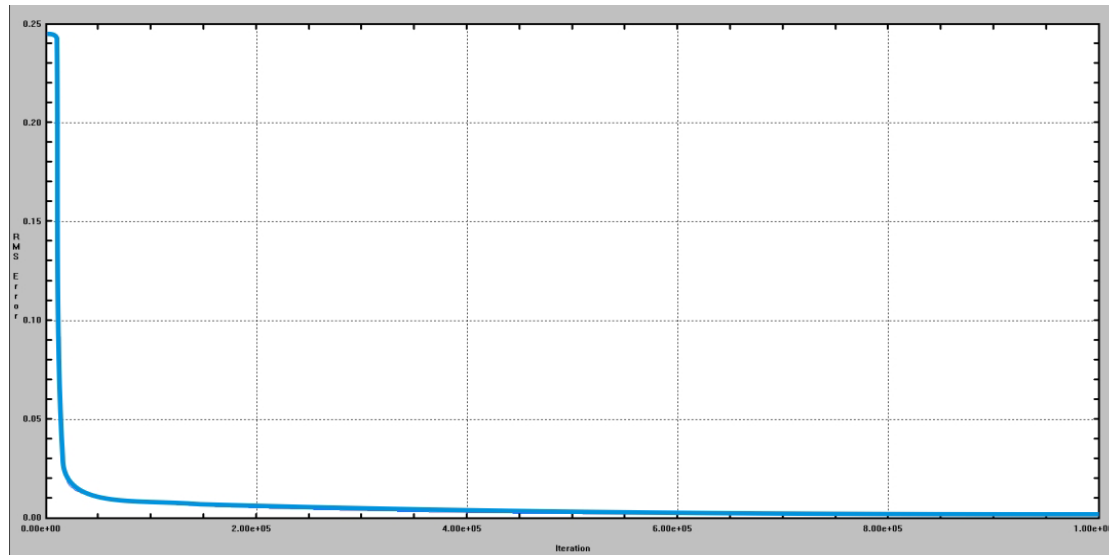


Figure 4. Root Mean Square Error of training versus net outputs

The back propagation training paradigm uses two controllable factors that affect the algorithm's rate of learning. The two factors are the learning rate coefficient (η), and the momentum factor, α . To optimize the rate at which a network learns, these factors must be set and/or adjusted properly during the training process. Just as there are limits to how fast a brain can learn ideas and concepts, there are also limits to the rate at which a network can learn. If a network is forced to learn at a rate that is too fast, instabilities develop that can lead to training divergence. On the ANN training, the η was unstable until the $6.00e+5$ interactions, at the same point when the ANN start to reach lower RMS value and it's shown on Figure 5. The best hybrid energy solution demonstrated by CES is a system based on the use of the national electric grid in conjunction with wind-powered generators and hydro turbines, for variables of wind speed and flow of 5,9 m/s and 19 l/s, respectively, with a value of NPV 1,26 millions of Euros with 3 wind-powered generators installed.

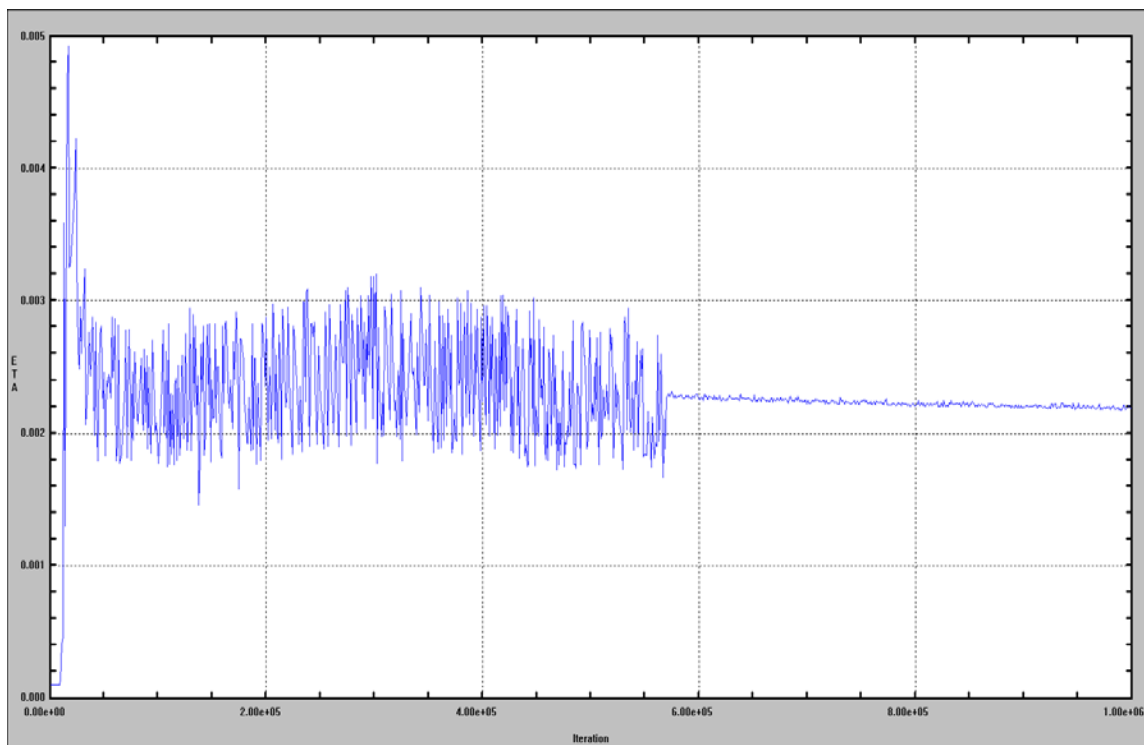


Figure 5. Learning rate coefficient adjustment.

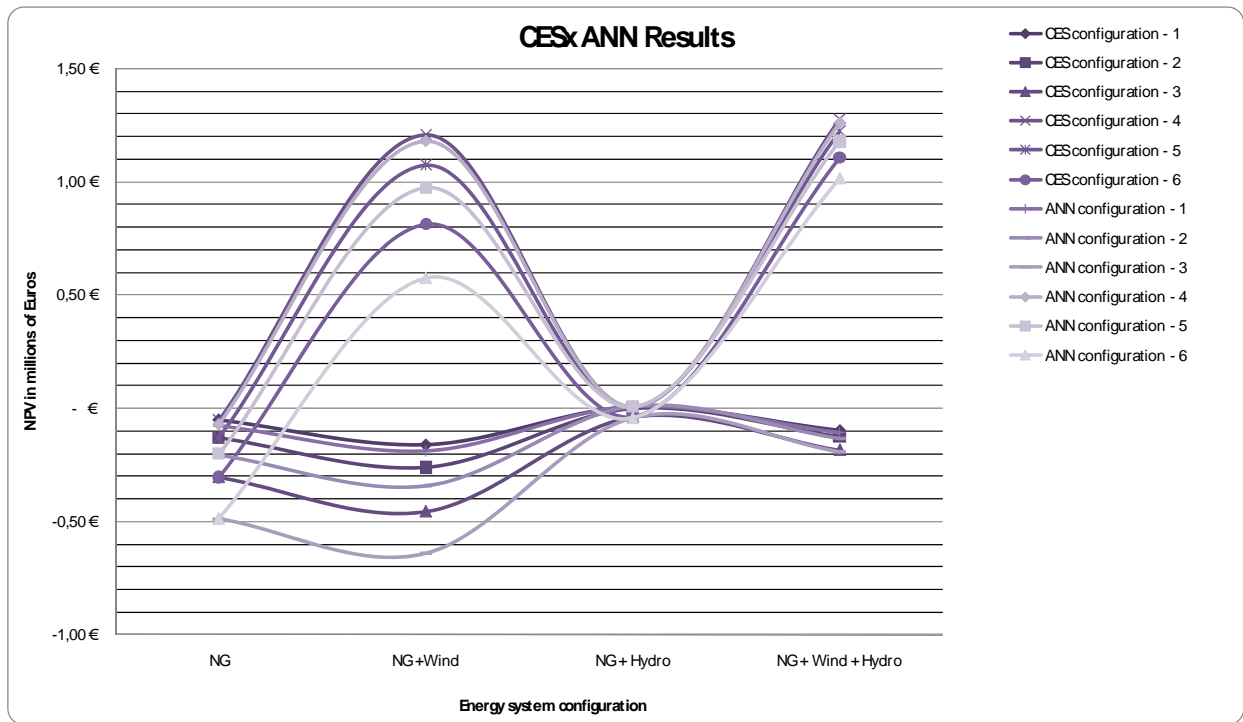


Figure 6. CES versus ANN results

The first stage of the study concerned in the composition of all results from CES with the ANN solution (Figure 6), demonstrating a good overlapping for different system configuration. The best energy system configuration is witch has the higher NPV value, resulting for NG+Wind+Hydro solution with the solution configuration 4. The solution from ANN model has a relative error of 1.19% comparing to CES solution. To determine the number of wind turbines for the best con-figuration, the neuron with the number of wind turbines on the winner configuration set is 3, the same achieved by CES software. A comparison between CES and ANN results on the energy system configuration (NG + Wind + Hydro) among the all data configurations is described in Figure 7, which confirm that the best solution correspond to the configuration 4. When the comparison is made between the neural network errors and the input sequence values demonstrate the system configuration solution output neuron 5 (NG + Wind + Hydro) present a good approach and is describing in Figure 8.

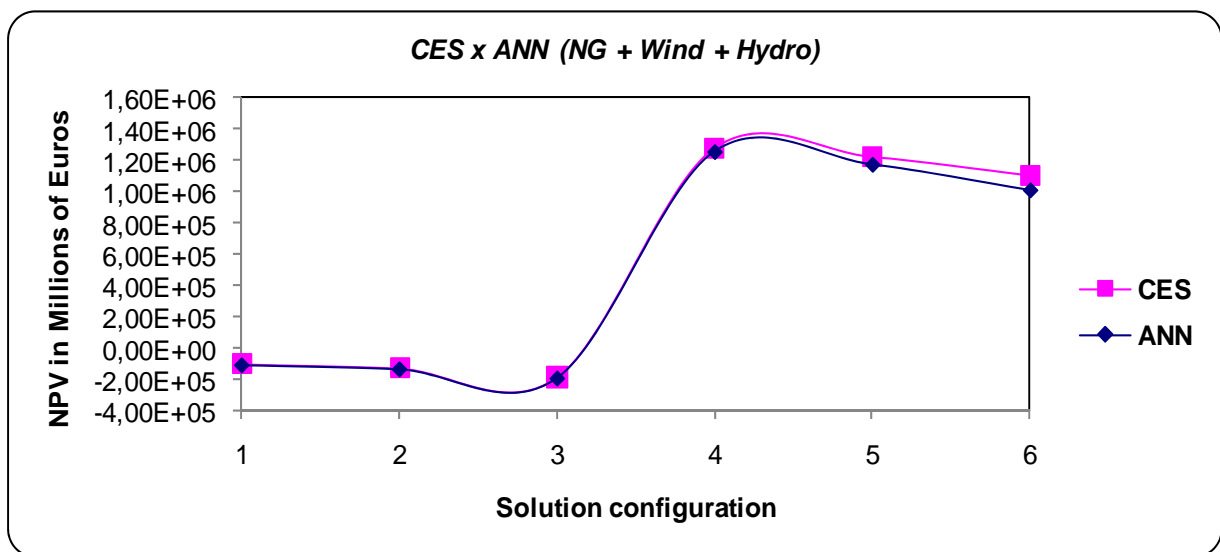


Figure 7. Comparison between CES and ANN results for different solution configuration of (NPV NG + Wind + Hydro).

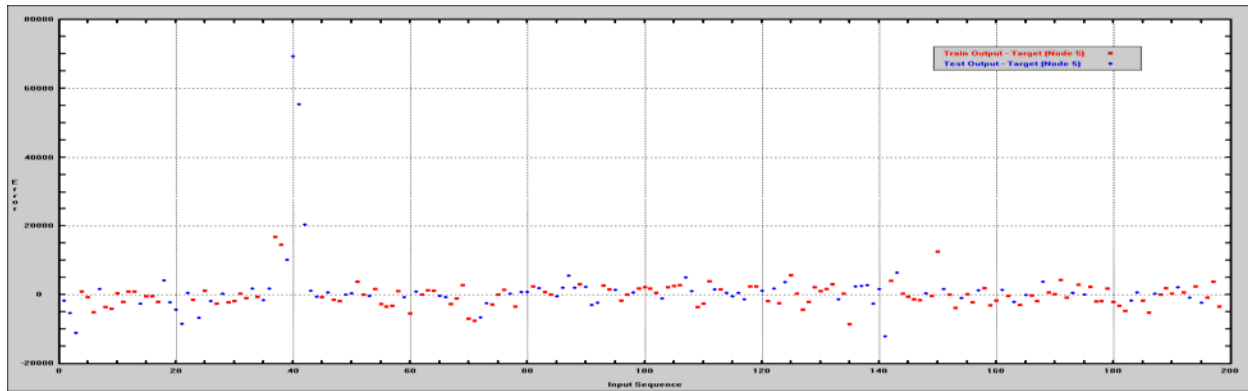


Figure 8. Network output error vs. Input sequence on output node 5 (NPV NG + Wind + Hydro solution)

5. Conclusion and recommendation

The best hybrid solution to be adopted in a particular supply system is a complex task, requiring the optimization of several objective functions subjected to multi-criteria analysis of penalty functions, which require advanced computational models where the development of additional tools presents some complexity.

It can be concluded by the results found in this study that the developed neural network behaves accordingly to the results obtained in CES, showing acceptable reliability in terms of possible solutions. For future work a larger number of characteristics of the system are intended to be analysed as well as including extended hybrid solutions, so that the model can be even more robust and comprehensive.

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