Hybrid energy system evaluation in water supply systems: artificial neural network approach and methodology

Fábio Gonçalves and Helena Ramos

ABSTRACT

Water supply systems are large consumers of energy mainly used in pumping stations and treatment plants, a major priority for water utilities being, therefore, the improvement of energy efficiency. The current research work presents a new methodology and a computational algorithm based on renewable energy concepts, hydraulic system behaviour, pressure control and neural networks for the determination of the best hybrid energy configuration to be applied in a typical water supply system. The artificial neural network (ANN) created to determine the best hybrid system uses scenarios with grid only supply, grid combined with hydro turbine, with wind turbine and mutual solution with hydro and wind turbine. The ANN is trained based on values obtained from a configuration and economical simulator model, as well as from a hydraulic and power simulator model. The results obtained show this ANN advanced computational model is useful for decision support solutions in the plan of sustainable hybrid energy systems that can be applied in water supply systems or others existent hydro systems allowing the improvement of the global energy efficiency.

Key words | artificial neural network, hybrid energy systems, renewable energy, sustainable energy solutions, water supply systems

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INTRODUCTION

A major concern in recent decades for managers of water supply systems has been to reduce the energy consumption caused by pumping, which is strongly affected by the influence of climate change on patterns of water consumption/supply. The recent increase in the price of oil has made the search for means to generate energy using alternative, renewable sources in a hybrid configuration a valuable energy solution, in particular associated with the level of water consumption.

The world economy is directly linked to energy and its rational use is necessary to produce a reasonable quality of life. According to Koroneos *et al.* (2003), renewable sources are used to produce energy with high efficiency and significant social and environmental benefits. Renewable energy includes hydro, wind, solar and many others. Variable weather and environmental conditions limit the ability of renewable sources to supply energy continuously, when only one source is considered. Such problems may be averted by integrating various sources, i.e. creating hybrid energy solutions, thus greatly reducing the irregularities and uncertainties of energy production. According to Wu *et al.* (2009), China's need for energy to continue its economic growth is enormous. China is already one of the biggest consumers of energy in the world, and it is imperative that new methods of energy production are developed, to reduce dependence on conventional sources (i.e. fossil fuels). Increasing energy consumption and the desired reduction in use of fossil fuels because of declining resources and increasing harmful effects of pollution are among the most important reasons for conducting research in renewable and sustainable solutions.

Hybrid solutions are suitable for water supply systems that need to decrease the cost of electricity consumed. These solutions, when installed in water systems, take advantage of power production based on its own available flow energy, as well as on locally available renewable

sources, saving on the purchase of energy produced by fossil sources and contributing to reduction of the greenhouse effect. According to recent studies, the option to mix complementary energy sources like wind, solar and hydropower seems to be a solution to mitigate the irregularity of energy supply when compared with only one source of renewable energy (Vieira & Ramos 2008, 2009; Moura & Almeida 2009; Ramos & Ramos 2009a, b).

A sustainable energy system has commonly been defined in terms of its energy efficiency, reliability and environmental impacts. The basic requirement for an efficient energy system is its ability to generate enough power for world needs with affordable price, clean supply, safety and reliablility. On the other hand, the typical characteristics of a sustainable energy system can be derived from new policy definitions and objectives as they are quite similar in all industrialised countries. The improvement of the efficiency of energy production and the guarantee of reliable energy supply now seem to be common interests of the developed and developing countries (Alanne & Saari 2006).

This study aims to present an artificial neural network (ANN) model for the optimization of the best hybrid solution configuration applied to a typical water supply system.

BACKGROUND REVIEW

Basic concepts

Unlike conventional power generation, a hybrid system by definition is one that uses an alternative arrangement of technologies to achieve similar objectives, i.e. a constant and reliable energy supply. Renewable energy takes many forms, each one being associated with strengths and weaknesses, depending on the local situation and configuration type. When different forms are combined in a complementary way, an integrated solution could be configured to achieve the best energy efficiency improvement in any water system. The need for a constant reliable energy supply is fundamental, as well as the amount required (Seare 1999), therefore a hybrid solution is ideal. As is well known, renewable energy production is generally weather dependent, and its likely output can be predicted but not guaranteed. An alternative to the reduction of energy use

is to decrease costs, and to lessen dependence on weather factors by using complementary sources based on wind generation, photovoltaic, micro hydro, among other local available sources.

Demands for water, environmental targets and energy savings have become the main concerns of water managers over recent years and promise to be more and more important in the near future. The energy for pumping to deliver water to populations represents the main cost for water companies (Vieira & Ramos 2008). Using renewable energy creates multiple public benefits, such as environmental improvement (reduction of greenhouse emissions, air and noise pollution), reduction of energy price volatility effects on the economy and improvement of the national economy, as fossil energy is vulnerable to political instabilities, trade disputes, embargoes and other disruptions. In contrast, renewable energy increases economic productivity through more efficient production processes (Menegaki 2008). Renewable sources represent a viable option for power generation even though there are some geographical and environmental restrictions. They are available locally and their use results in significant environmental benefits by reducing emissions of CO_2 and other pollutants; contributes to job creation, yielding social benefits and economic cohesion; stimulates competitiveness in the industry, increases security and stability in the decentralised energy supply and reduces imports.

Through the European Union Directive 2001/77/EC, the indicative target for Europe for production from renewable sources is 22% of the electricity consumed. It is expected to achieve this objective through quotas taken by different member states (European Commission 2001) and Portugal is an excellent example in this regard.

Hybrid energy systems

In the past decade hybrid energy has received much attention as it is a viable alternative technology compared with energy supply based entirely on hydrocarbon fuels, giving flexibility of energy management and a longer life cycle (Gupta *et al.* 2006; Vieira & Ramos 2008).

An example of a hybrid energy network integrated into a drinking water system is when a group of pumps can be supplied with electricity through renewable sources, taking into

account the water consumption pattern, the electricity tariff, environmental factors and the system characteristics, such as storage water regularisation volume. Commonly these systems work based only on a national energy grid. However, alternative solutions can be adopted. During peak hours, when the higher costs are specified in the electricity tariff, the system could be supplied by renewable sources (e.g. micro-hydro turbines installed in water gravity pipelines complemented by wind or solar energy). When energy prices are lower, the national electric grid is used to pump water, and when energy prices are higher, the renewable sources could be used to power the system for pumping. Whenever there is water consumption, the turbine is operating to supply pumping stations, treatment plants or to sell surplus energy to the national grid.

Kenfack et al. (2009) designed a micro-hydro-photovoltaic hybrid system for rural electrification; they compared different combinations of component sizes and quantities, and explored how variations in resource availability and system characteristics affect the costs of installing and operating different systems for electrification of a remote area in a developing country. The results achieved recommend use of such hybrid system at similar sites. Currently hybrid power systems can be found in many forms, e.g. as a energy source for rural desalination plants (Setiawan et al. 2009), a renewable resource of power for grid-connected applications in Iraq (Dihrab & Sopian 2010) or as a multi-energy system in buildings (Fabrizio et al. 2010).

Modeling conditions

Gupta et al. (2006), Vieira & Ramos (2008) and Ramos & Ramos (2009b) show that the modeling of hybrid energy research systems and their applications in the decentralised mode are still quite limited. The models currently applied are generally based on only one or two available sources. Further attempts to develop optimum energy solutions based on different sources for meeting energy targets are also quite restricted. So, the application of models for matching the estimated future energy demand with a complementary combination of sources at decentralised level is an important aim of modeling research. Gupta et al. (2010) have developed a mixed integer linear mathematical programming model (time-series) to determine optimal

operation and configuration including the assessment of the economic penetration levels of photovoltaic array area, and cost optimization for a hybrid energy generation system in a rural area electrification in a decentralized mode.

Integrated urban water management is an important and critical matter in all cities and countries. Many objectives and criteria, such as the satisfaction of urban water consumers, the national benefits and social hazards, must be considered in integrated urban water management.

Fattahi & Fayyaz (2010) presented a mathematical model using compromise programming to optimize a multi-objective problem in integrated in water management. Objectives involving water distribution cost, leakage water and social satisfaction level were considered to evaluate the performance and efficiency of the model, and the results demonstrated its capability to solve the problem. Compromise programming belongs to a class of multicriteria analytical methods called 'distance-based' methods which identifies solutions closest to the ideal one by some distance measure.

Software models (e.g. HOMER, PVSYST) have been used by various researchers to design and research alternative energy solutions (Gabrovska et al. 2004; Gupta et al. 2006; Barsoum & Vacent 2007; Vieira & Ramos 2008; Ramos & Ramos 2009a). These tools are usually developed by European or American research centres and may be supported by energy companies. MATLAB® can be used for optimization modeling to manage the water and energy in water supply systems. Vieira & Ramos (2009) used linear and non-linear programming to develop an optimization tool to obtain the best hourly operation, according to the electricity tariff, with water consumption and inlet discharge, for a pump-storage system supplied by wind energy. A model for prediction and optimization of energy management of hybrid-type systems with specific operational controls is needed urgently.

Artificial neural networks

ANN have been used to model the degradation of water in water distribution systems (Sakarya & Mays 2000; Castronuovo & Lopes 2004; Turgeon 2005; Jafar & Shahrour 2007). The research has been considered promising,

providing a strong base for the development of a financial-economical model, which used with the degradation model, is able to give an integrated approach to optimizing intervention strategies in water distribution systems. Even with the limitations, the prediction performance has proven to be rather good in the short and medium term.

Sakarya & Mays (2000) carried out analysis of water quality using an ANN model. For simulating the water quality inside reservoirs, ANN models are preferred to physical models, as the latter tend to demand a great deal of laboratory or field efforts, when compared with ANN, which can be combined with other optimisation techniques, such as dynamic programming, reducing time required and costs.

As part of the POWADIMA (Potable Water Distribution Management) 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 (Jamieson et al. 2007; Rao & Alvarruiz 2007). Because the use of a complex hydraulic simulation model is somewhat different for real-time operations, as a result of imposed computational time consumption, the approach adopted has been to capture its domain knowledge in a far more efficient way by means of ANN (Chaves et al. 2004).

A neurofuzzy algorithm was used as a powerful tool for risk-of-failure analysis in two case studies; the combination of ANNs and fuzzy logic is extremely effective for the detection of patterns in underlying data and in the conversion of these patterns to knowledge and generic rules, which can assist in risk-of-failure analysis and preventive maintenance of water distribution (Christodoulou & Deligianni 2010). Al-Alawi et al. (2007) developed an ANN-based model for the optimum operation of an integrated hybrid renewable energy based water and power supply system, demonstrating that an ANN can be used with high degree of confidence to predict the control strategies.

METHODOLOGY

The development of an ANN in order to capture the best energy model domain from a configuration model and an economical simulator (CES), in a much more efficient way, is based on the following observations: (i) a robust database has to be developed to create the input and output data set that will be used in ANN development and training; (ii) the data has to be analysed to determine a structure that fits the problem and then to train and validate the ANN. A flowchart describing the procedures of the designed ANN is shown on Figure 1.

Data set

The data used in this study were calculated by means of a CES model, which gives an optimised ranking of the best hybrid solution for each particular case, based on an economic analysis for the production and consumption of energy.

This data set was organized to evaluate the use of hybrid solutions in water distribution systems based on wind turbine, micro-hydro and the national grid. Hence, the range of data was defined in order to suit the installation of such energy converters. The data range for flow, power head and water levels variation in reservoirs were used in a hydraulic and power simulator (HPS) to determine the power consumed by the pump and the power produced in a micro-hydro turbine installed in a gravity pipe branch, whenever there is available energy in the system. These data were included in the CES model with renewable resources performance characteristics to determine the best hybrid solution to be selected. One of the data sources used in the CES was the wind turbine power curve of a selected wind turbine (Figure 2(a)), the local wind source along an average year for the region under analysis (Figure 2(b)) and the wind annual average speed applied to the wind turbine.

Energy simulation

In order to obtain the data needed to train the ANN, the HOMER and the micro-power optimisation model was used to determine the best hybrid solution for an extended range of values in order to create a robust data set to be used in the ANN training and evaluation. For this purpose the data used cover the values needed to have a small hydro turbine installed in a water distribution system and a wind turbine system consistent with Portugal's wind profile.
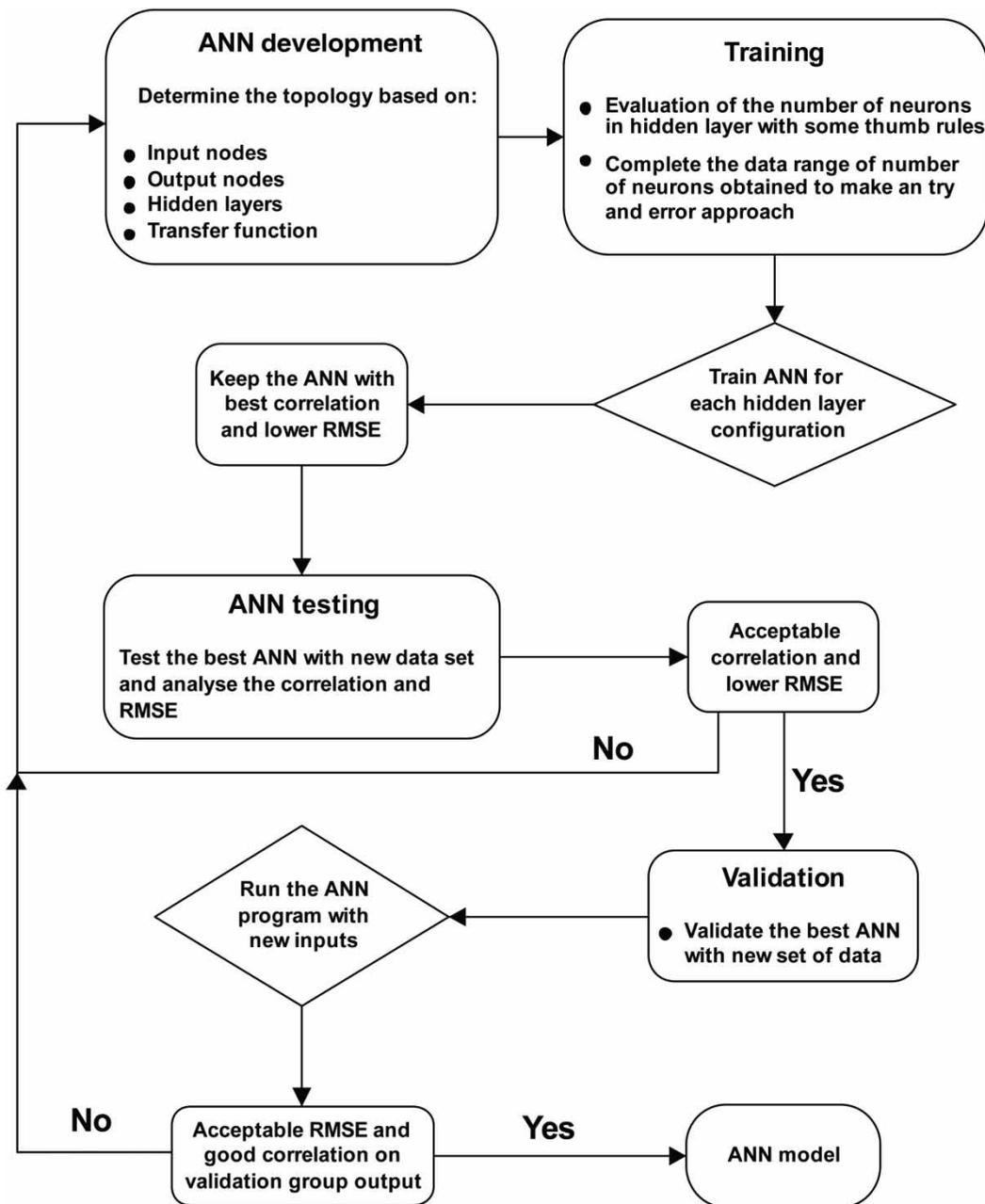
Figure 1 | Flowchart for the developed ANN model.

Analysis results from a water distribution system, with an Enercon E33 wind turbine and a micro-hydro turbine, is shown in Figures 3 and 4. The ANN creation prioritises the use of an Enercon wind turbine because this ANN model is for regions with low wind speeds rates, like Lisbon. These turbines give reasonable energy production output at low wind speeds but can also take advantage of daily peaks (Ramos & Ramos 2010). Figure 3 demonstrates the hydro capacity of the system with a sensitivity analysis performed on some parameters. Figure 4 shows the sensitivity analysis made for the wind energy production.

The optimisation model HOMER exhibits the best energy hybrid solutions for the whole range of appropriate
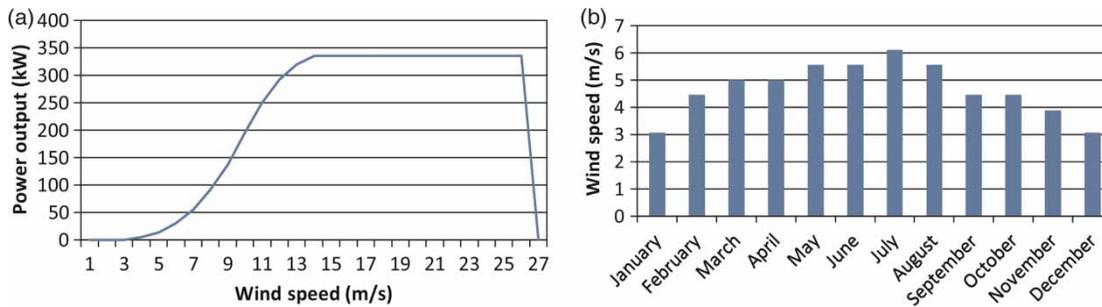
Figure 2 | Wind energy: (a) wind turbine power curve for an Enercon E33, (b) Wind source for 1 year in the Lisbon region.
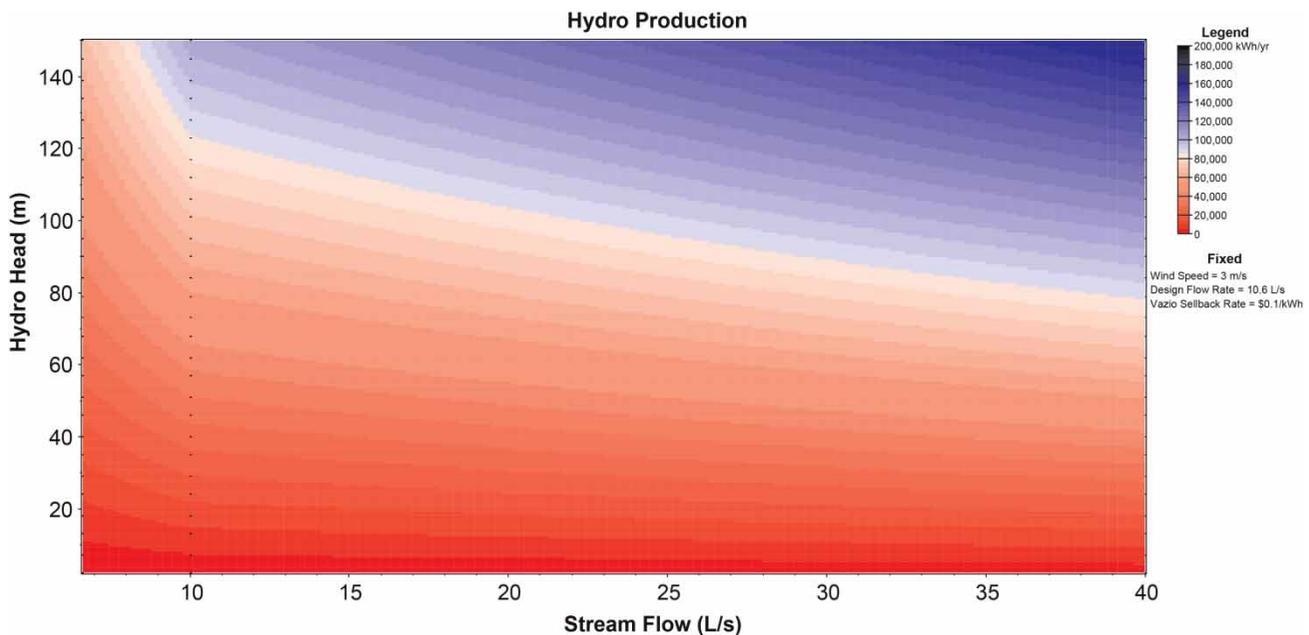

Figure 3 | Hydro capacity sensitivity analysis.

values to be applied in a water distribution system (Figure 5). For low wind speeds the best solution demonstrated by HOMER is using the hydro turbine connected with the grid but once the wind speed increases, the use of wind turbines combined with hydro turbines become feasible for the system. The sensitivity analysis for the best solution for all the hydro heads available is the same, as shown in Figure 5.

In Table 1 the data set range is fixed and used with HOMER to determine the inputs and outputs of the developed ANN. The data were used to calculate all energy and economic parameters to be included in the HOMER model to complete the necessary data to train the ANN.

Based on a basic data range, depending on the system characteristics (Table 1) and auxiliary hydraulic and energy formulations, the complete input data were then obtained (Table 2): (1) pump power (KW); (2) pump energy consumption (KW/d); (3) hydro-turbine power (KW) – average output; (4) flow (m^3/s) – annual average flow; (5) gross head (m); (6) pumping head (m); (7) head losses (m); (8) power net head (m); (9) design pumping flow rate (L/s); (10) wind speed (m/s) – annual average; and (11) wind turbine power (KW) – annual average output.

HOMER uses the net present cost to determine the best hybrid system among all the solutions. The total net present
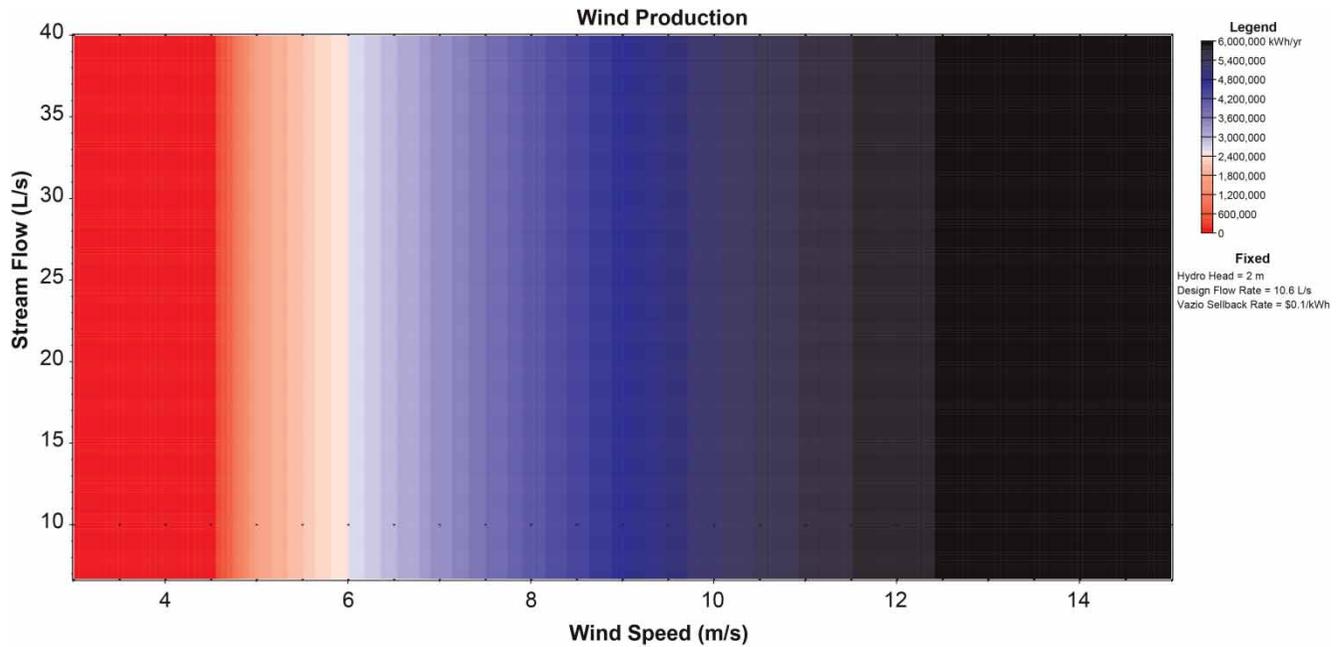
Figure 4 | Wind production sensitivity analysis.
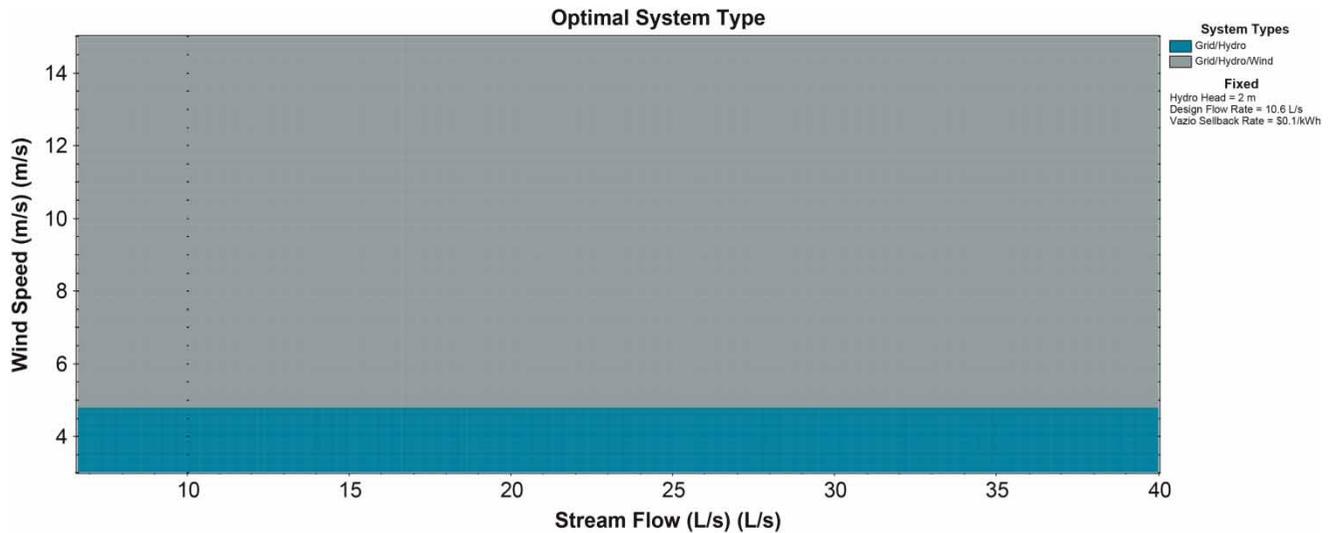
Figure 5 | Optimal sensitivity analysis for energy hybrid solution.

cost of a system is the present value of all the costs that it incurs over its lifetime, minus the present value of all the revenue that it earns over its lifetime. Costs include capital costs, replacement costs, operation and maintenance (O&M) costs, fuel costs, emissions penalties, and the costs of buying power from the grid. Revenues include salvage value and revenue from grid sales. HOMER calculates the total net present cost using the following equation:

$$C_{\mathrm{NPC}} = \frac{C_{\mathrm{ann,tot}}}{\mathrm{CRF}(i, R_{\mathrm{proj}})} \tag{1}$$

where: $C_{\mathrm{ann,tot}}$ = total annualised cost ($/yr); CRF = capital recovery factor; i = interest rate (%); R_{proj} = project lifetime (yr)

Table 1 | Basic data set range used in CES

Wind speed annual average (m/s)	Flow (L/s)	Power net head (m)	Gross head (m)
1.5	10	2	10
2.0	20	7	16
2.5	30	13	21
3.0	40	18	27
3.5	50	24	32
4.0	60	29	38
4.5	70	35	43
5.0	80	40	49
5.5	90	46	54
6.0	100	51	60
6.5	150	57	66
7.0	200	62	71
7.5	250	68	77
8.0	300	73	82
8.5	350	79	88
9.0	400	84	93
9.5	450	90	99
10.0	500	95	104
10.5	550	101	110
11.0	600	106	116
11.5	650	112	121
12.0	700	117	127
12.5	750	123	132
13.0	800	128	138
13.5	850	134	143
14.0	900	139	149
14.5	950	145	154
15.0	1,000	150	160

and the CRF is calculated using the following equation:

$$\text{CRF}(i, N) = \frac{i \cdot (1+i)^N}{(1+i)^N - 1} \tag{2}$$

where: N = number of years; i = real interest rate (%).

To develop the comparison data set, a 5% interest rate and 25 years equipment lifetime were used in Equation (2); the calculation results in a CRF 0.071, indicating €1,000 loan at 5% interest could therefore be paid back with 25 annual payments of €71. The present value of the 25 annual payment of €71 is then represented by €1,000.

$$\text{CRF}(0.05, 25) = \frac{0.05 \cdot (1+0.05)^{25}}{(1+0.05)^{25} - 1} = 0.071$$

The capital costs used in the modeling was €2,500 for the hydro turbine with O&M of €250/year and €660,000 for the wind-turbine with O&M of €6,600/year.

The total net present cost is HOMER's main economic output. HOMER ranks all systems according to total net present cost (Lilienthal 2004). In ANN creation the total net present value (NPV) is used, which is the inverse value to the NPC. The total net present cost sensitivity analysis computed in HOMER for a stream flow of 40 L/s is shown in Figure 6.

At the end of the modeling process the input data set was built in a matrix of [11 × 19,602] (Table 2), which involves the interaction of all values needed to create a complete data set that represent all values of flow and wind speed (matrix of [5 × 19,602] in Table 3) to develop a base to create the ANN prediction that as a result gives the NPV of each hybrid solution configuration, as well as the number of wind turbines to be installed. The ANN data set was then created to be used in water distribution systems to determine the NPV of each hybrid system evaluated for each type of configuration (e.g. grid, grid + hydro, grid + wind, grid + hydro + wind).

ANN development and validation

MATLAB® was used for the ANN development in this study. The creation of an ANN should comprise the following steps: (i) patterns definition; (ii) network implementation; (iii) identification of the learning parameters; and (iv) training, testing and validation processes.

A neural network model of hybrid energy must be compared with an energy CES using the following procedures: use the CES to obtain data to use in the training process and in reliable neural network tests, together with a HPS for a large range of flow rates, gross heads, pumping and power heads and wind velocities. These data, available in Ramos & Ramos (2009b), use the HPS to hydraulically balance the water supply system, in a village in Portugal,

Table 2 | Input data set for the system characteristics used in ANN

Pump power (kW/h)	Pump energy consumption (kW/d)	Hydro-turbine power (kW)	Flow (m³/s)	Gross head (m)	Pumping head (m)	Head losses (m)	Power net head (m)	Design pumping flow rate (L/s)	Wind speed (m/s)	Wind turbine power (kW)
0.245	2.205	0.157	0.01	10	18	8	2	16	3	15
0.322	2.895	0.587	0.01	16	24	8	7	16	3	15
0.398	3.584	1.016	0.01	21	29	8	13	16	3	15
0.475	4.274	1.446	0.01	27	35	8	18	16	3	15
0.552	4.964	1.876	0.01	32	41	8	24	16	3	15
0.628	5.653	2.306	0.01	38	46	8	29	16	3	15
0.705	6.343	2.735	0.01	43	52	8	35	16	3	15
1.103	9.927	3.752	0.02	32	41	8	24	32	3.5	24
1.256	11.306	4.611	0.02	38	46	8	29	32	3.5	24
1.410	12.686	5.471	0.02	43	52	8	35	32	3.5	24
1.563	14.065	6.330	0.02	49	57	9	40	32	3.5	24
1.716	15.444	7.190	0.02	54	63	9	46	32	3.5	24
1.869	16.823	8.049	0.02	60	69	9	51	32	3.5	24
2.023	18.203	8.909	0.02	66	74	9	57	32	3.5	24
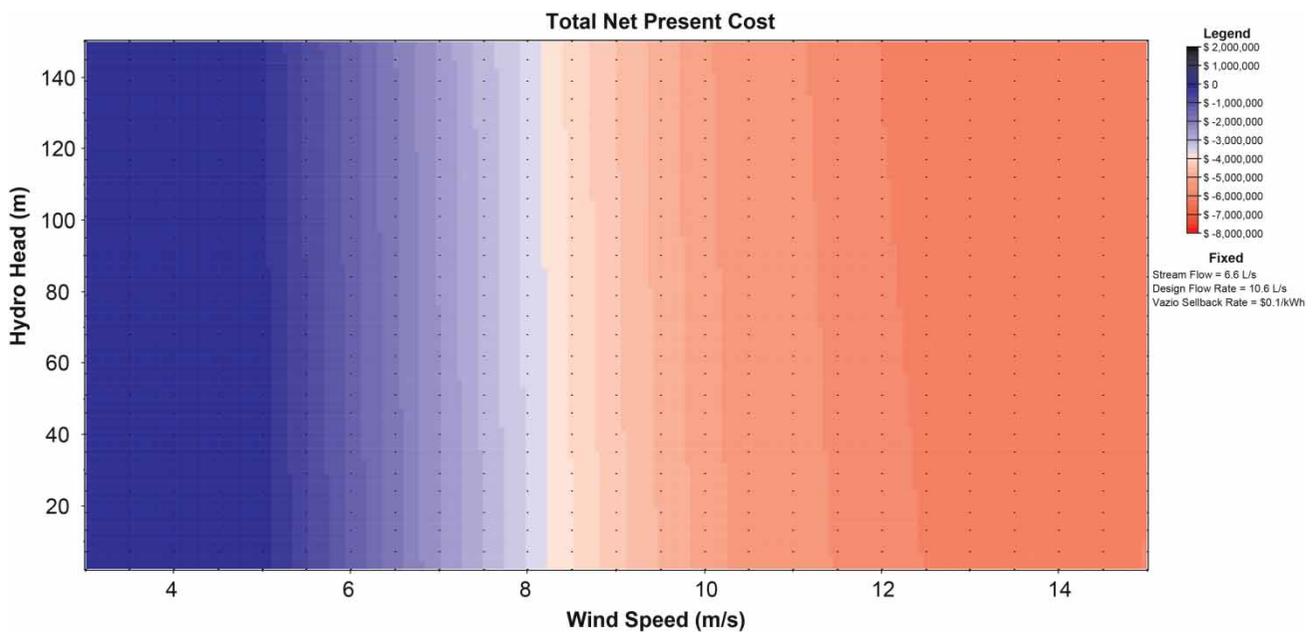
Figure 6 | Total net present cost sensitivity analysis for energy hybrid solution.

determining the hydraulic behaviour of the whole system including the most suitable pump and turbine operation for each flow condition.

When the ANN code runs, it shows the process of training and simulation for each system characteristic. In the training mode the configuration parameters are introduced to the ANN. The parameters are standard limits (maximum and minimum), number of neurons in the hidden layer, limit number of epochs, final error desired, validation rate and activation function used in the hidden layer. The range of

Table 3 │ Input data set for the best economic configuration used in ANN

NPV (€) grid	NPV (€) grid + hydro	NPV (€) grid + wind	NPV (€) grid + hydro + wind	Wind turbine installed
−59.00	1,812.00	−571,464.00	−569,553.00	1
−78.00	6,617.00	−571,495.00	−564,747.00	1
−96.00	12,391.00	−571,526.00	−558,973.00	1
−115.00	17,197.00	−571,557.00	−554,168.00	1
−133.00	22,971.00	−571,588.00	−548,394.00	1
−152.00	27,776.00	−571,619.00	−543,588.00	1
−170.00	33,550.00	−571,650.00	−537,814.00	1
−189.00	38,356.00	−571,680.00	−533,009.00	1
−207.00	44,130.00	−571,712.00	−527,235.00	1
…	…	…	…	…
−226.00	48,935.00	−316,043.00	−266,690.00	2
−244.00	54,710.00	−316,077.00	−260,916.00	2
−263.00	59,514.00	−316,111.00	−256,110.00	2
−282.00	65,289.00	−316,146.00	−250,337.00	2
−300.00	70,094.00	−316,180.00	−245,531.00	2
−319.00	75,868.00	−316,214.00	−239,757.00	2
−337.00	80,674.00	−316,248.00	−234,951.00	2
−356.00	86,447.00	−316,282.00	−229,177.00	2
−374.00	91,253.00	−316,317.00	−224,372.00	2
…	…	…	…	…
−393.00	97,027.00	109,886.00	207,679.00	3
−411.00	101,832.00	109,850.00	212,483.00	3
−430.00	107,606.00	109,813.00	218,258.00	3
−448.00	112,411.00	109,778.00	223,062.00	3
−467.00	118,185.00	109,741.00	228,838.00	3
−485.00	122,991.00	109,706.00	233,644.00	3
−504.00	128,765.00	109,669.00	239,416.00	3
−522.00	133,570.00	109,633.00	244,223.00	3
−541.00	139,344.00	109,597.00	249,997.00	3
−559.00	144,150.00	109,561.00	254,802.00	3

normalised amplitude in the output of a neuron is written as the closed interval [−0.85, 0.85].

In this study the normalised amplitude adopted promotes a best prediction to higher or lower values than those data of input data set parameters used in the creation. To determine the number of neurons used in the ANN, a trial and error solution is also adopted. Initially based on rules of thumb, several approaches to the best number are used. These rules include empirical formulas of

Baum-Hauser and Hetcht-Nielsen (McCord-Nelson & Illingworth 1991; Lin *et al*. 2004; Valença 2009).

$$N_{\text{hid}} \leq \frac{N \cdot \varepsilon_{\text{train}}}{N_{\text{inp}} + N_{\text{out}}} (\text{Baum} - \text{Hauser}) \tag{3}$$

where N_{hid} is the number of neurons in the hidden layer, N is the number of examples used to train the network, $\varepsilon_{\text{train}}$ is the allowed error in the training, N_{inp} is the number of neurons in the input layer and N_{out} is the number of neurons in the output layer.

$$N_{\text{hid}} = 2 \cdot (N_{\text{inp}} + 1) (\text{Hetcht} - \text{Nielsen}) \tag{4}$$

The numbers of neurons in the hidden layer found using these rules of thumb were 12 neurons (Equation (3)), or 24 neurons (Equation (4)). Demuth & Beale (2002) state that ANNs 'are also sensitive to the number of neurons in their hidden layers. Too few neurons can lead to underfitting. Too many neurons can contribute to overfitting, in which all training points are well fit, but the fitting curve takes wild oscillations between these points'. To avoid overfitting (number of nodes or too many neurons in the hidden layer, the accuracy of the approximation for training could be higher as required, while the prediction accuracy for data beyond the training set would be very poor) and underfitting (usually caused by too few nodes or number of neurons in hidden layer, identified by the divergence of the network during the training), we adopt Equation (2) using 24 neurons in the hidden layer.

The neuronal topology adopted is $11 \times 24 \times 1$, where 11 is the number of inputs, 24 is the number of neurons in the hidden layer and 1 is the output result. In fact, to determine the best solution five ANNs are need to achieve the five solutions from the CES model (i.e. the system operation only with energy from the grid, a combination of grid and hydro production, grid and wind turbine, grid, hydro and wind turbine).

With the best ANN configuration for each possible hybrid system and new data set for inputs, a validation process is made and the results are verified in terms of correlation and relative error among the values of CES model and the ANN, as presented in Table 4.

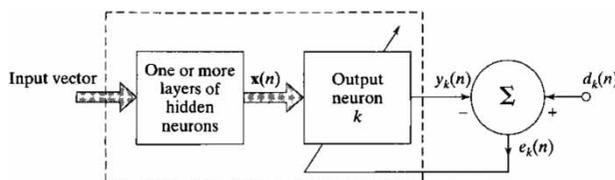**Table 4** | Relative ANN error concerning to CES model

Hybrid system solutions	Grid	Grid + Hydro	Grid + Wind	Grid + Hydro + Wind
Correlation	0.99999121	0.99996283	0.99999695	0.99999538
Relative error (best solution)	0.22%	0.08%	0.09%	0.16%
Mean relative error	0.74%	1.80%	2.51%	2.02%

ANN ANALYSIS AND DISCUSSION

In order to guarantee the ANN has good correlation and lower root mean square error for all configurations, validation performances and correlation graphics were analysed. The ANN developed uses the learning method rule, where the simple case of a neuron k constitutes the only computational node in the output layer of a neural network (Figure 7). Neuron k is driven by a signal vector $x(n)$ produced by one or more layers of hidden neurons, which are themselves driven by an input vector applied to the source nodes (i.e. input layer) of the neural network. The argument n denotes discrete time, or more precisely, the time steps (epochs) of an iterative process involved in adjusting the synaptic weights of neuron k. The output signal of neuron k is denoted by $y_k(n)$. This output signal, representing the only output of the neural network, is compared with a desired response or target output, denoted by $d_k(n)$. Consequently, an error signal, denoted by $e_k(n)$, is produced. By definition, the error signal is given by:

$$e_k(n) = d_k(n) - y_k(n) \tag{5}$$

The error signal $e_k(n)$ actuates as a control mechanism, the purpose of which is to apply a sequence of corrective adjustments to the synaptic weights of a neuron k. The corrective adjustments are designed to make the output signal $y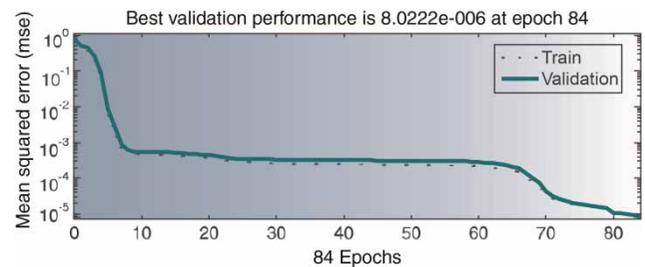_k(n)$ come closer to the desired response $d_k(n)$ in a step-by-step manner. This objective is achieved by minimising a cost function or index of performance, $\varepsilon(n)$, defined in terms of $e_k(n)$ as:

$$\varepsilon(n) = \frac{1}{2} e_k^2(n) \tag{6}$$

So, $\varepsilon(n)$ is the instantaneous value of the error energy. The step-by-step adjustments to the synaptic weights of a neuron k are continuous until the system reaches stabilization (i.e. the synaptic weights are essentially stabilized) or the error e desired is finally achieved. At that point the learning process is finalized.

The goal line is a representation of the area where the value of the error described in the initial training for the desired error appears and the epochs is the number of times that the ANN adjusts the synaptic weights to reach the desired error. As previously explained in the process of training in continuous adjustment of the synaptic weights, the best error value is always the same error value imposed in the training setup parameters or a lower value, if the ANN converges. In Figure 8 the best error determined in ANN training is always lower than the error of the training setup, showing the convergence of the trained ANN.

Then the ANN is used with new data sets and the results are analysed to obtain the best hybrid system configuration being compared with those obtained by CES. With the

Figure 7 | Scheme of a neural network highlighting a single neuron in the output layer (Haykin 1998).

Figure 8 | Best validation performance and correlation in grid with hydro and wind turbine configuration.
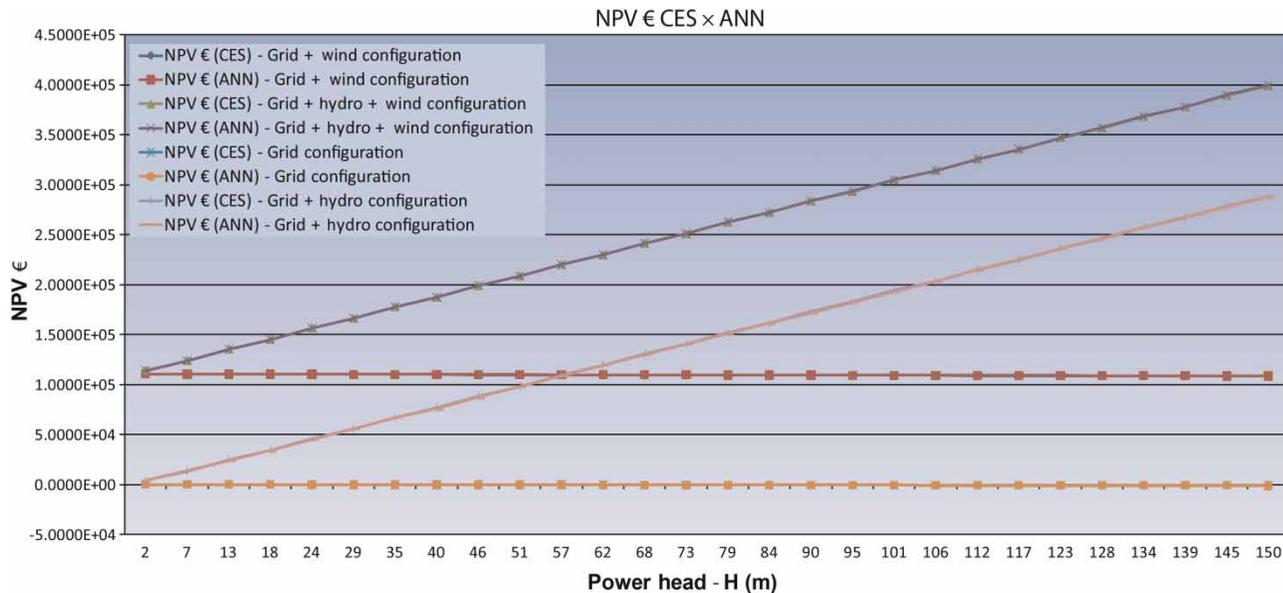
Figure 9 │ NPV results for CES and ANN.

results found in ANN modeling, the relative error among CES and ANN values is analysed. The best economic solutions (based on NPV index) compared between the CES and ANN is shown in Figure 9.

In this comparison process, for the data set input considered in this study it was verified that the best economic result calculated with the ANN corresponds to grid, hydro and wind configuration with three wind turbines installed for a NPV of €3.99E + 5. CES results for the same situation present a NPV of €4.00E + 5, for a wind speed of 5 m/s, a flow of 20 L/s and a power net head of 150 m. The relative error calculated is 0.16% and the ANN solved the problem in no more than 2 s against 45 min for the CES model for the same number of variables.

CONCLUSIONS

The present research work aims at the prediction analysis of the best energy system configuration, depending on the renewable sources available at each site, and the optimisation of operating strategies of a water supply system, taking into consideration different points of view such as operational, technical and hydraulic performance. For this purpose, an integrated software tool was developed based on the following procedures: (i) an ANN was

created to determine the best hybrid energy system arrangement; (ii) for the ANN training process a CES was used; (iii) a HPS to describe the hydraulic behaviour and hydro-mechanical operation was also applied; (iv) a performance assessment tool based on an optimisation module to minimise pumping costs and maximise the hydraulic reliability and energy efficiency was then implemented.

Hence, the objective is essentially to present an ANN that captures the knowledge domain in a much more efficient way than a CES, ensuring good reliability and the best hybrid energy solution to improve energy efficiency in water distribution systems even though ANN models always have limitations in terms of range of data and type of renewable source solution.

A study of implementation of hydro power in water supply systems shows that it can be a good method to improve the energy efficiency of these systems.

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