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Inverse neural network for optimal performance in polygeneration systems

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ABSTRACT

In this paper, inverse neural network (ANNi) is applied to optimization of operating conditions or parameters in energy processes. The proposed method ANNi is a new tool which inverts the artificial neural network (ANN), and it uses a Nelder-Mead optimization method to find the optimum parameter value (or unknown parameter) for a given required condition in the process. In order to accomplish the target, first, it is necessary to build the artificial neural network (ANN) that simulates the output parameters for a polygeneration process. In general, this class of ANN model is constituted of a feedforward network with one hidden layer to simulate output layer, considering well-known input parameters of the process. Normally, a Levenberg–Marquardt learning algorithm, hyperbolic tangent sigmoid transfer-function, linear transfer-function and several neurons in the hidden layer (due to the complexity of the process) are considered in the constructed model. After that, ANN model is inverted. With a required output value and some input parameters it is possible to calculate the unknown input parameter using the Nelder-Mead algorithm. ANNi results on three different applications in energy processes showed that ANNi is in good agreement with target and calculated input data. Consequently, ANNi is applied to determine the optimal parameters, and it already has applications in different processes with a very short elapsed time (seconds). Therefore, this methodology can be useful for the controlling of engineering processes.

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1. Introduction

Today, the artificial neural network (ANN) has great applications to describe processes involved in engineering, as an example: performance of a water purification process integrated on a heat transformer. This type of model (ANN) simulates the phenomenon of the process, considering well-known parameters. Nevertheless, in the large majority of engineering processes it is needed to work with optimal input and output parameters for the performance of the process.

In order to obtain optimal operating conditions or parameters, a mathematical description of such a process is required. There are some works which calculate optimum operating conditions using different mathematical models [1–4]. However, calculation of optimal parameters becomes sometimes difficult and requires special software, especially when process complexity is considered.

The progress of neurobiology has allowed searchers to build mathematical models of neurons to simulate the process behavior. Neural networks are recognized as good tools for dynamic modeling [5,6]. The point for using this specific model includes three reasons involved in engineering processes: (1) working without any assumptions about the nature of underlying mechanisms, (2) making the most of their abilities to take into account non-linearities and iterations between variables [5], and (3) gaining time, because this type of model lays on simple arithmetic operations allowing rapid calculations. A neural model can always be identified based on the perceptron structure, with only one hidden layer, for either steady-state or dynamic operations [7,8]. Commonly, neural networks are adjusted (or trained), so that a particular input leads to a specific target output. In such a situation, the network is adjusted, based on a comparison of the output and the target, until the network output matches the target. Today, neural networks can be trained to solve problems that are difficult for conventional computers or human beings. An elementary neuron with R inputs is shown in Fig. 1. Each input is weighted with an appropriate W. The sum of the weighted inputs and the bias conform the input to the transfer-function (f) to generate their output. Normally, the hyperbolic tangent sigmoid transfer-function is applied for the hidden layer and linear transfer-function for the output layer [9].

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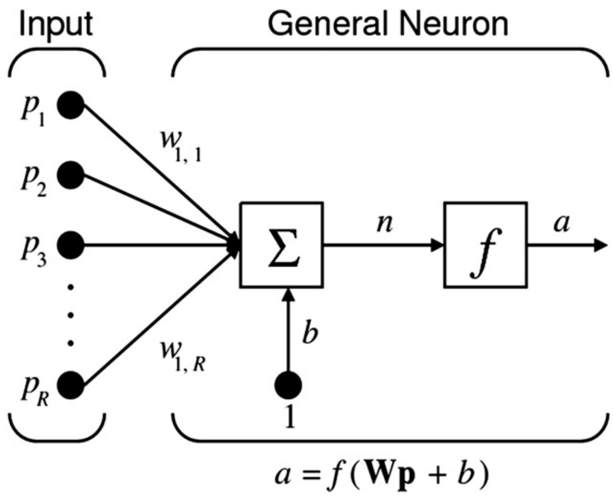

Fig. 1. Elementary neuron.

Massive applications of Feed-Forward Back-Propagation neural networks are reported in the literature for engineering processes, for example: applications in control, robotics, pattern recognition, power systems, optimization and signal processing [10]. Furthermore, Kalogirou [10] mentioned that ANN has been used in energy problems in the field of solar energy, for modeling the heat-up response of a solar steam-generating plant, for the estimation of a parabolic trough collector intercept factor, for the estimation of a parabolic trough collector local concentration ratio and for the design of a solar steam generation system. Sözen et al. [11] developed an ANN for the analysis of ejector-absorption refrigeration systems. Sözen and Arcaklioğlu [12] proposed also ANN to determine the exergy losses of an ejector-absorption heat transformer. Recently, Vasi·kaninova et al. [13] applied an ANN for predictive control on a heat exchanger. Du et al. [14] proposed an ANN to model the back pressure of an air cooled steam turbine, one of the most important parameters of the power generating unit. Conceição and Afonso [15] used an ANN to predict air temperature fields inside refrigeration cabins. The authors [15] compared the ANN model with a CFD code obtaining as results that ANN produced a lower error than CFD. Therefore, when modeling such as processes, the skill of neural network to integrate complex relationships between process parameters and product quality (output parameters) becomes of great interest. Nevertheless, in many cases in the engineering processes, it is necessary to have the optimal or required output parameters, but the optimal input parameters are unknown. Consequently, this paper presents the strategy or new tool to obtain the optimal global parameters in the engineering process. This methodology is based by an inverse neural network and a Nelder-Mead optimization method.

2. Inverse neural network (ANNi)

A general neural network is shown in Fig. 2 which is constituted by hyperbolic tangent (tanh) or sigmoid function (tansig) in the hidden layer and linear transfer-functions in the output layer. Then, the output is given by,

$$\text{output}_{\{k\}} = y_{\{k\}} = purelin\left(\sum_{s=1}^{S}\left[\text{LW}_{\{k,\,s\}}\cdot\left(tansig\left(\sum_{r=1}^{R}\text{IW}_{\{s,\,r\}}\cdot p_r + b1_{\{s\}}\right)\right)\right] + b2_{\{k\}}\right) \tag{1}$$

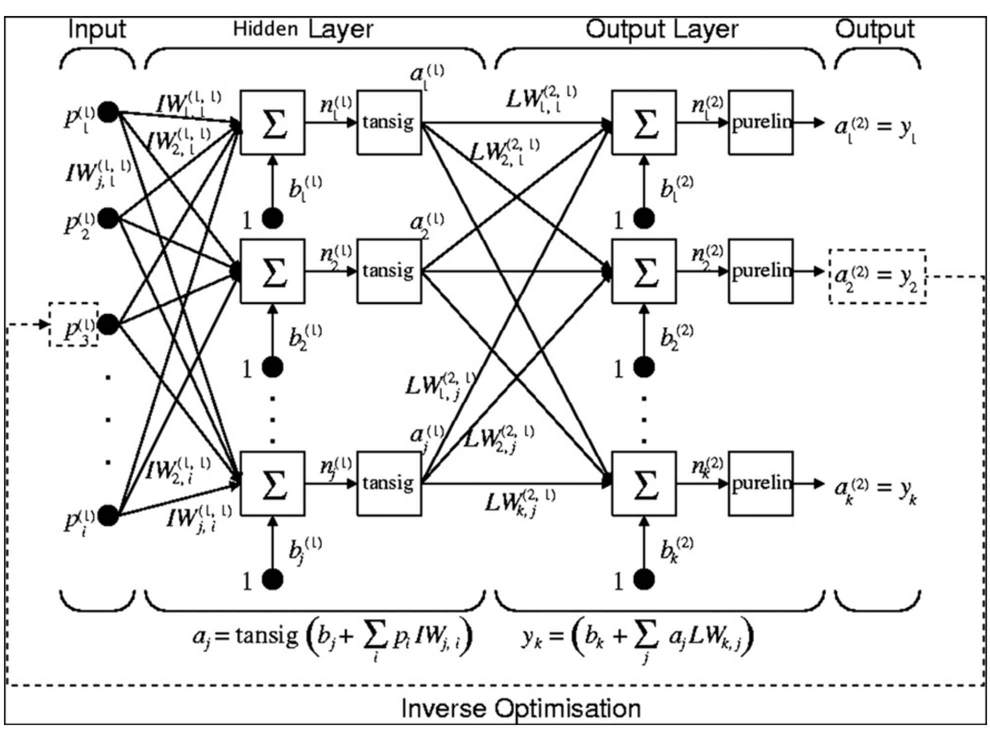

Fig. 2. General neural network model and inverse.

If the definition of *purelin* and *tansig* functions are used, $y_{\{k=2\}}$ is given by,

$$y_{\{2\}} = \sum_{s=1}^{S}\left[\mathrm{LW}_{\{2,s\}}\cdot\left(\frac{2}{1+\exp\left(-2\left(\sum_{r=1}^{R}\mathrm{IW}_{\{s,r\}}\cdot p_r + b1_s\right)\right)}-1\right)\right]+b2_{\{2\}} \tag{2}$$

Let $p_{\{r=3\}}$ be the input to be estimated and $k=2$ the required output $y_{\{2\}}$. Then

$$y_{\{2\}} = b2_{\{2\}} - \sum_{s=1}^{S}\mathrm{LW}_{\{2,s\}} + \sum_{s=1}^{S}\left[\frac{2\cdot\mathrm{LW}_{\{2,s\}}}{1+\exp\left(-2\left(\mathrm{IW}_{\{s,3\}}\cdot p_3 + \sum_{r\neq 3}^{R}\mathrm{IW}_{\{s,r\neq 3\}}\cdot p_{\{r\neq 3\}} + b1_s\right)\right)}\right] \tag{3}$$

The next function (Eq. (4)) is to be minimized to zero to find the optimal input(s) parameter(s) in a general ANN, in this case, x is the p_3 value to be computed to zero by an optimization method.

$$f(x) = b2_{\{2\}} - \sum_{s=1}^{S}\mathrm{LW}_{\{2,s\}} - y_{\{2\}} + \sum_{s=1}^{S}\left[\frac{2\cdot\mathrm{LW}_{\{2,s\}}}{1+\exp\left(-2\left(\mathrm{IW}_{\{s,3\}}\cdot x + \sum_{r\neq 3}^{R}\mathrm{IW}_{\{s,r\neq 3\}}\cdot p_{\{r\neq 3\}} + b1_s\right)\right)}\right] \tag{4}$$

Therefore, optimization can be done using the Nelder-Mead method.

3. Nelder-Mead method

The Nelder-Mead method is a generally used nonlinear optimization algorithm. This method is a numerical method to minimize to zero an objective function in a multi-dimensional space. This algorithm is a direct search method that does not use numerical or analytic gradient [16]. It attends to minimize a scalar-valued nonlinear function of n real variables using only function values, without any derivative information. The method uses the concept of simplex, which is a polyhedron of $N+1$ in N dimensions. Simplices are a line, a triangle and tetrahedron in one-, two-, and three-dimensional space, respectively, and so forth [17]. The method approximately finds a local optimal solution with N variables when the objective function varies smoothly. Nelder-Mead generates a new test position by extrapolating the behavior of the objective function measured at each test point arranged as a simplex. Then, the algorithm chooses to replace one of these test points with the new test point. Thereby, a new simplex is generated with a single evaluation of the objective [17].

4. Inverse neural network considering one neuron in the hidden layer in ANN model

It is very important to remark that in the case that only one neuron has been considered in the hidden layer of an ANN model; it is possible to obtain the inverse response with an analytical solution to two cases:

- If *tansig* and *purelin* are considered, and $k=1$, $R=1$:

$$\mathrm{output}_1 = \mathrm{LW}_{\{1,1\}}\cdot\left(\frac{2}{1+\exp(-2\cdot(\mathrm{IW}_{\{1,r\}}\cdot p_r + b1_l))}-1\right)+b2_1 \tag{5}$$

This can be transformed into:

$$\mathrm{output}_1 = \frac{2\cdot\mathrm{LW}_{\{1,1\}}}{1+\exp(-2\cdot(\mathrm{IW}_{\{1,r\}}\cdot p_r + b1_l))} - \mathrm{LW}_{\{1,1\}} + b2_1 \tag{6}$$

Let $p_{\{r=1\}}$ be the input parameter to be calculated when one output parameter is required. Then:

$$p_1 = -\frac{1}{2\cdot\mathrm{IW}_{\{1,1\}}}\mathrm{In}\left(\frac{\mathrm{LW}_{\{1,1\}} - \mathrm{output}_1 + b2_1}{\mathrm{output}_1 + \mathrm{LW}_{\{1,1\}} - b2_1}\right) - \frac{b1_1}{\mathrm{IW}_{\{1,1\}}} \tag{7}$$

- If *logsig* and *purelin* are considered, and $k=1$, $R=1$:

$$\mathrm{output}_l = \mathrm{LW}_{\{1,1\}}\cdot\left(\frac{1}{1+\exp(-\mathrm{IW}_{\{1,1\}}\cdot p_1 + b1_1)}\right)+b2_1 \tag{8}$$

Then the input parameter can be calculated from Eq. (9):

$$p_1 = \frac{b1_1 - \mathrm{In}\left(\frac{\mathrm{LW}_{\{1,1\}}}{\mathrm{output}_1 - b2_1}-1\right)}{\mathrm{IW}_{\{1,1\}}} \tag{9}$$

Therefore, according to Eq. (1), that it is possible to simulate the outputs values, when input parameters are well known. However, in many cases, the problem is that ANN predicted output values which are not satisfactory in the system, and therefore, it is necessary that its inputs variables are well known when giving a required or satisfactory output. Consequently, the new control strategy which is proposed here using ANN model applied to energy systems. The proposed strategy uses an inverse of neural network and the Nelder-Mead optimization algorithm to find the optimal input values for the required output value. Then in this ANNi methodology, as mentioned above, the required output value is well-known.

Three applications of ANNi were performed to optimize different energy processes. First, a water purification process integrated to a heat transformer was studied and optimized aimed to increase the performance. Second, experimental single-state heat transformer results were analyzed based on second law of thermodynamic with the aim of decrease the irreversibility of the process. Finally, a compressor's performance in the scope of turbo-machinery was optimized. The three proposed ANNi models for the energy processes consider more than one neuron in the hidden layer due to the complexity of each applicacion, therefore, it is necessary to apply an optimization method to obtain the input paramater.

5. Optimal performance for a water purification process integrated to a heat transformer

Fig. 3 shows a schematic diagram for a heat transformer integrated to a water purification process. Useful heat (Q_{AB}) is the result of the reaction between working fluid steam and absorbent solution (which comes from the evaporator and generator, respectively). After this process, a diluted Water/LiBr solution, goes to the generator. In the generator, the aqueous solution receives a quantity of heat (Q_{GE}) from an external heat supply. Under these conditions, working fluid steam leaves the generator and goes through a condenser where it loses heat (Q_{CO}) and the fluid is condensed. This condensate goes to the evaporator where external heat (Q_{EV}) is supplied, and the working fluid evaporates at high pressure and goes to the absorber. At the same time, a concentrated Water/LiBr solution goes to the absorber, and at this point, the cycle starts again. The absorber gives the unique useful heat delivered (Q_{AB}) in the heat transformer. Q_{AB} is used to heat the impure water until it reaches its boiling point and partly evaporates. The two phases (liquid water and steam) leave the absorber and are separated through a phase separator. The liquid phase returns to the suction pump, and the steam produced goes through an auxiliary condenser where heat is transferred as steam condenses while the heat source stream is heated. The coeffient of performance (COP) is defined as the ratio of heat delivered in the absorber divided by the heat load supplied to the generator plus evaporator ($COP = Q_{AB}/(Q_{GE} + Q_{EV})$).

Hernández et al. [18] proposed a neural network model (Fig. 3) which exhibits an efficiency of 0.998% in predicting COP values for the water purification process integrated to an absorption heat transformer with energy recycling. This developed ANN model had three neurons in the hidden layer (51 weights and 4 biases) and considering 16 input parameters (different temperatures, pressures and concentrations). The proposed equation by Hernández et al. [18] is:

$$COP = \sum_{s=1}^{S}\left[LW(1,\ s)\cdot\left(\frac{2}{1+\exp\left(-2\cdot\left(\sum_{r=1}^{R}(IW(s,\ r)\cdot p_r)+b1(s)\right)\right)}-1\right)\right]+b2 \tag{10}$$

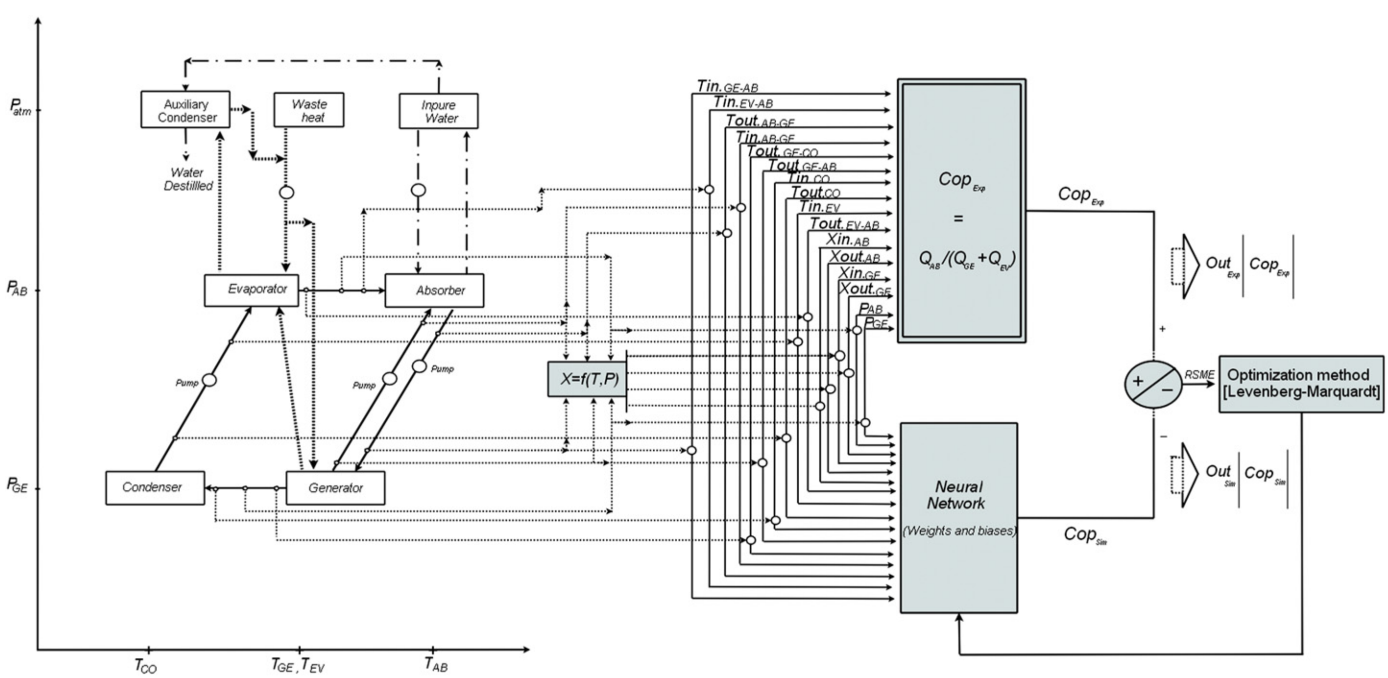

Fig. 3. Recurrent network architecture for COP values and procedure used for neural network learning.

where the number of neurons in the input layer is 16. According to model given by Eq. (10), it is possible to simulate the COP in the energy process, when input parameters are well-known. However, in this process, it is important to find out, for instance, which optimal pressure in the Absorber (input number 15) is needed for a required coefficient of performance. Therefore, the strategy to estimate the optimal pressure in the Absorber was ANNi. The inverse of the artificial neural network (10) is the following Eq. (11) that calculates COP in the system with recycling energy.

$$\mathrm{COP} - b2_1 + \sum_{s=1}^{S} \mathrm{LW}_{(1,\,s)} = \frac{2\cdot \mathrm{LW}_{(1,\,1)}}{1+e^{\left(X1-2\cdot \mathrm{IW}_{(1,\,15)}P_{15}\right)}} + \frac{2\cdot \mathrm{LW}_{(1,\,2)}}{1+e^{\left(X2-2\cdot \mathrm{IW}_{(2,\,15)}P_{15}\right)}} + \frac{2\cdot \mathrm{LW}_{(1,\,3)}}{1+e^{\left(X3-2\cdot \mathrm{IW}_{(3,\,15)}P_{15}\right)}} \tag{11}$$

where

$$X1 = -2\cdot\left(\sum_{r\neq 15}^{R} \mathrm{IW}_{(1,\,r\neq 15)}\cdot P_{(r\neq 15)} + b1_{(1)}\right) \tag{12}$$

$$X2 = -2\cdot\left(\sum_{r\neq 15}^{R} \mathrm{IW}_{(2,\,r\neq 15)}\cdot P_{(r\neq 15)} + b1_{(2)}\right) \tag{13}$$

$$X3 = -2\cdot\left(\sum_{r\neq 15}^{R} \mathrm{IW}_{(3,\,r\neq 15)}\cdot P_{(r\neq 15)} + b1_{(3)}\right) \tag{14}$$

$S = 3$, $R = 16$, $l = 1$ and Table 1 shows the weights (IW and LW) and biases (b1 and b2), and the input parameters, P (temperatures, pressures and concentrations) are reported by Hernández et al. [18]. In order to minimize to zero this Eq. (11), an optimization method (Nelder-Mead Simplex Method) was used to calculate Absorber pressure (P_{AB}). The optimization method finds the minimum of a scalar function of several variables, starting at an initial estimate. This is generally referred to as unconstrained nonlinear optimization. Optimization method starts at the point $P_{15}0$ (initial value) and finds a local minimum P_{15} of the function described in Eq. (11).

An example of this application is shown to calculate the required P_{AB} considering the experimental data reported by Hernández et al. [18], which values are obtained from experimental test database. The normalized input values are used as they appear in the experimental data [18] and we only want to calculate the P_{AB} value: $T_{\text{inGE-AB}} = 0.89$, $T_{\text{inEV-AB}} = 0.80$, $T_{\text{outAB-GE}} = 0.87$, $T_{\text{inAB-GE}} = 0.88$, $T_{\text{outGE-CO}} = 0.89$, $T_{\text{outGE-AB}} = 0.894$, $T_{\text{inCO}} = 0.59$, $T_{\text{outCO}} = 0.767$, $T_{\text{inEV}} = 0.388$, $T_{\text{outEV-AB}} = 0.804$, $X_{\text{inAB}} = 0.908$, $X_{\text{outAB}} = 0.908$, $X_{\text{inGE}} = 0.9085$, $X_{\text{outGE}} = 0.909$, $P_{AB} = ?$, $P_{GE} = 0.904$; and an output value, COP = 0.39. Then, with weights and biases of Table 1, and the optimization method, it was possible to calculate the optimum P_{AB}, which was $P_{\text{ANNi-AB}} = 10.8851$ in Hg. In order to test this value, $P_{\text{ANNi-AB}}$ is compared to $P_{\text{exp-AB}}$ of the experimental data. The reported experimental value was $P_{\text{exp-AB}} = 11$ in-Hg [18] and consequently the error is given as: error = $[(P_{\text{exp-AB}} - P_{\text{ANNi-AB}})/P_{\text{exp-AB}}] \times 100$. Therefore, in this case, an error of 1.04% was obtained which is very acceptable. The elapsed time to calculate this pressure (P_{AB}) from this methodology (ANNi and Nelder-Mead Simplex Method) is just 42.18 s. This time is good enough to control the process, because, when an operating condition has been modified (for example: P_{AB} changed under stable state conditions), the delay in stabilizing the system is of 5 min.

6. Optimal performance for a single-state heat transformer

The single-stage heat transformer consists of an evaporator, a condenser, a generator, an absorber, and an economizer. Fig. 4 shows the operation of this experimental system in a plot of temperature against pressure. Similarly, a quantity of waste heat Q_{GE} is added at a relatively low temperature T_{GE} to the generator to vaporize the working fluid from the weak salt solution containing a low concentration of absorbent. The vaporized working fluid flows to the condenser delivering an amount of heat Q_{CO} at a reduced temperature T_{CO}. The liquid leaving the condenser is pumped to the evaporator in the higher pressure zone. The working fluid is then evaporated by using a quantity of waste heat Q_{EV} which is added to the evaporator at an intermediate temperature T_{EV}. Next, the vaporized working fluid flows to the absorber where it is absorbed in a strong salt solution containing a high concentration of absorbent from the generator delivering heat Q_{AB} at a high temperature T_{AB}. Finally, the weak salt solution is returned to the generator to preheat the strong salt solution in the economizer before repeating the cycle again. The experimental single-stage heat transformer of 2 kW of power supplied into the generator and evaporator, and about 1 kW of power in the absorber was constructed entirely in stainless steel 316 (see Fig. 4). The generator and evaporator are of the stagnant pool type were heat is supplied by means of electrical heaters immersed in the solution and water respectively. The condenser is a tank with a coil inside which condenses the water vapor coming from the generator. The absorber is of a vertical falling film type where oil circulates inside the tubes to remove the heat at the higher temperature produced by the absorption of the water vapor into the strong solution. The

Table 1
Adjusted parameters to predict COP.

$\mathrm{IW}_{(s,1-8)}$							
1.0471	1.6234	8.541	1.7987	7.1516	1.196	1.09	2.5118
20.071	6.462	46.46	6.3265	26.4226	16.547	14.638	37.4539
3.7487	0.113	3.5127	0.545	0.6408	0.3451	0.0254	0.00001
$\mathrm{IW}_{(s,9-16)}$							
0.003	2.342	242.393	159.4	172.5	20.837	19.476	65.588
0.3227	4.4175	216.870	135.7784	115.0829	10.2770	17.5255	47.0385
0.0032	0.1114	0.4314	7.1419	12.6125	3.2912	0.1576	1.1184
$\mathrm{LW}_{(l,s)}$							
0.186	0.0239	0.8825					
$\mathrm{b1}_{(s,1)}$							
129.0939							
17.7516							
6.4906							
$\mathrm{b2}_{(l,1)}$							
0.2427							

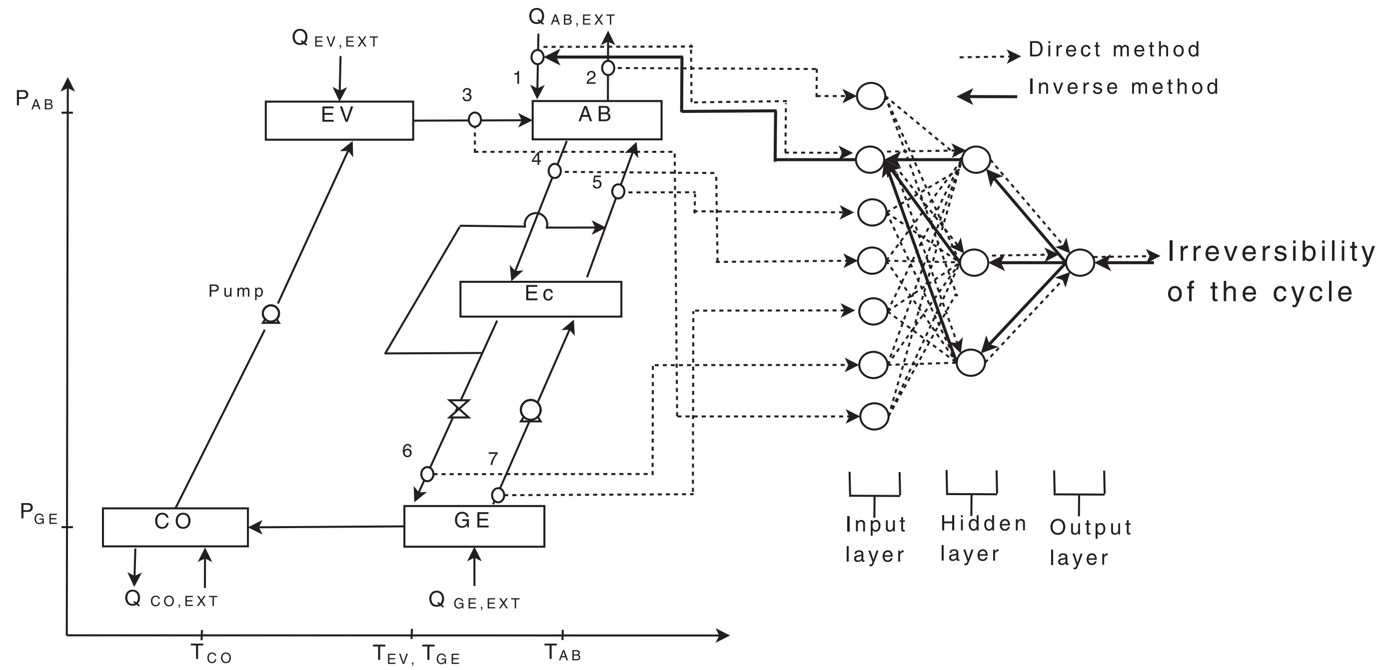

Fig. 4. Application of neural network inverse to an absorption heat transformer.

economizer is a concentric tube heat exchanger. The heat input was controlled by two variable transformers, each with a maximum power of 2 kW [19,20].

Colorado et al. [19] proposed an analysis based on first and second law of thermodynamics together with direct and artificial neural networks inverse (ANNi). The methodology has been used to decrease the total irreversibility of an experimental single-stage heat transformer. Fig. 4 shows a heat transformer representation in a T vs. P diagram and the ANN and ANNi methodology proposed.

It had three neurons in the hidden layer (24 weights and 4 biases). The equation proposed is:

$$A = I_{\text{cycle}} - b2_{(2,\,1)} + W_{o(2,\,1)} + W_{o(2,\,2)} + W_{o(2,\,3)} \tag{18}$$

$$B = -2 \times \Big(W_{i(1,\,1)} \times T_2 + W_{i(1,\,3)} \times T_3 + W_{i(1,\,4)} \times T_4 + W_{i(1,\,5)} \times T_5 + W_{i(1,\,6)} \times T_6 + W_{i(1,\,7)} \times T_7 + b1_{(1,\,1)}\Big) \tag{19}$$

$$C = -2 \times \Big(W_{i(2,\,1)} \times T_2 + W_{i(2,\,3)} \times T_3 + W_{i(2,\,4)} \times T_4 + W_{i(2,\,5)} \times T_5 + W_{i(2,\,6)} \times T_6 + W_{i(2,\,7)} \times T_7 + b1_{(2,\,1)}\Big) \tag{20}$$

$$I_{\text{total}} = \sum_{s=1}^{S}\left[\mathrm{LW}(1,\,s)\cdot\left(\frac{2}{1+\exp\left(-2\cdot\left(\sum_{r=1}^{R}(\mathrm{IW}(s,\,r)\cdot p_r)+b1(s)\right)\right)}-1\right)\right]+b2 \tag{16}$$

where the number of neurons in the input layer is $R = 7$ and $s = 3$. According to this proposed model (Eq. (16)), it is possible to simulate the total irreversibility in the energy process based in ANN, when input parameters are carefully registered. However, it is important to develop a strategy to decrease total irreversibility of the system and estimate the optimal inlet conditions in the heat transformer. The inverse of the artificial neural network as illustrated in (Eq. (17)), which calculates the total irreversibility in the system, based in the external temperature inlet from external heat flux (T_1).

$$f(T_{16}) = -A + \frac{2W_{o(2,\,1)}}{1+e^{(B+7.7936T_1)}} + \frac{2W_{o(2,\,2)}}{1+e^{(C+7.6766T_1)}} + \frac{2W_{o(2,\,3)}}{1+e^{(D-14.7320T_1)}} \tag{17}$$

where:

Table 2
Adjusted parameters to predict I_{total}.

IW						
7.6642	−3.8968	−15.7846	4.9652	−5.9405	13.3903	1.0362
5.9847	−3.8383	12.9651	1.1464	2.4265	−9.3331	−9.6583
6.2613	7.3660	−7.9201	2.0424	5.9771	7.8802	−1.5600
LW						
−2.4606	0.8924	0.0940				
b1						
14.2000						
3.2156						
−19.1499						
b2						
−0.9590						

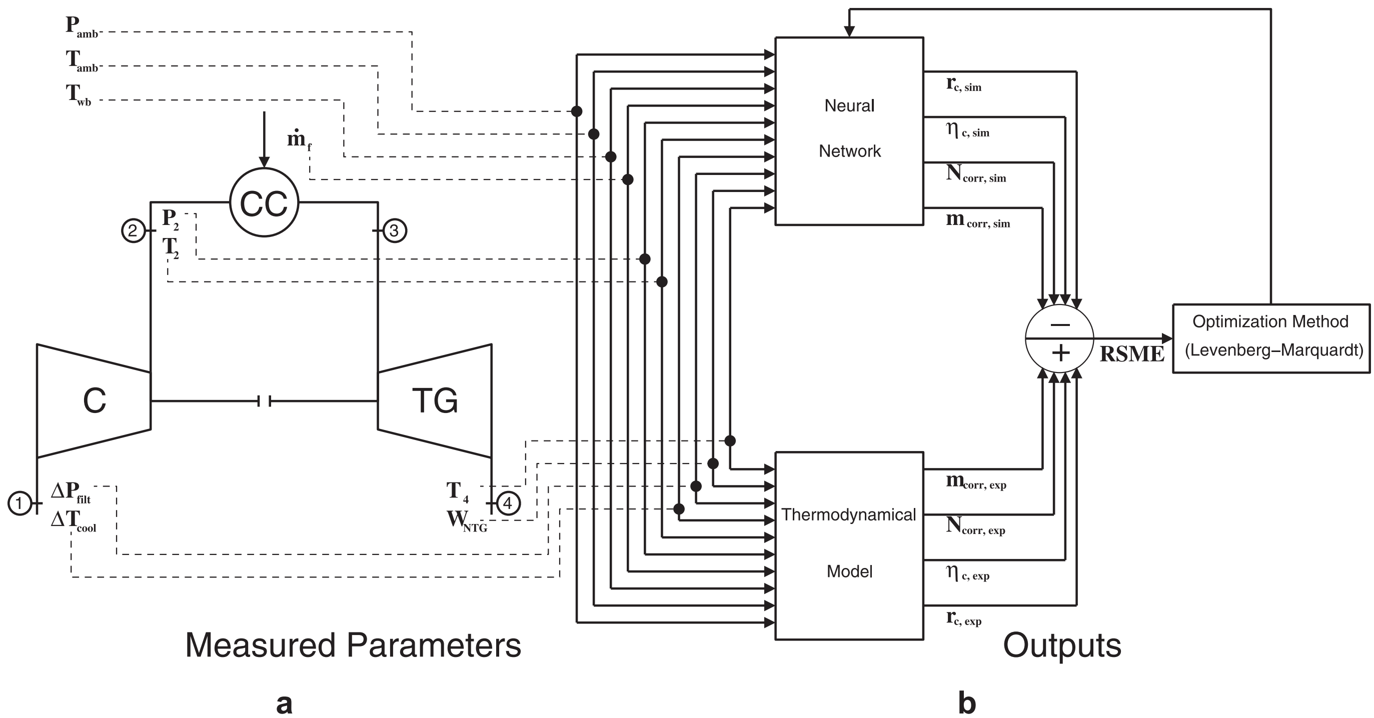

Fig. 5. (a) Gas turbine scheme with measurements positions for Siemens W501D and (b) Neural network model training.

$$D = -2 \times \Big(W_{i(3,\,1)} \times T_2 + W_{i(3,\,3)} \times T_3 + W_{i(3,\,4)} \times T_4 + W_{i(3,\,5)} \times T_5 + W_{i(3,\,6)} \times T_6 + W_{i(3,\,7)} \times T_7 + b1_{(3,\,1)}\Big) \quad (21)$$

In this case, a set of parameters is available for exergy analysis for an absorption heat transformer reported by Colorado et al. [19]. Experimental conditions were used with applied ANNi. For example: in order to a required output value $I_{cycle} = 87.19$ W, with input values: $T_2 = 76$ °C, $T_5 = 85.20$ °C, $T_4 = 87.20$ °C, $T_7 = 78.50$ °C, $T_6 = 80.87$ °C, $T_3 = 59.80$ °C and T_1 are unknown. With weights and biases of Table 2, it is possible to find the optimum external temperature inlet for the absorber to get the required output irreversibility. It is possible using the optimization method (Nelder-Mead Simplex). The outcome value was $T_{ANNi\text{-}1} = 79.34$ °C. Consequently, to test it, the experimental value is $T_{exp\text{-}1} = 78$ °C. Similarly, error $= ((T_{exp\text{-}1} - T_{ANNi\text{-}1})/T_{exp\text{-}1}) \times 100$ then we have a discrepancy minor to 1.72%.

7. An optimal compressor performance in the scope of turbomachinery

Inverse neural network has been applied not only in heat transformer devices. The last 20 years represent a large growth for gas turbine technology. As for the increase in gas turbine efficiency, it depends on two basic parameters, enhanced efficiency in (a) pressure ratio, (b) firing temperature. Cortés et al. [21] describe a way to optimize parameters related to compressor performance used in turbomachinery, based on artificial neural networks inverse. Fig. 5a shows a compressor (C), combustor (CC) and turbine (TG) modules of a gas turbine plant. Then, measurements of a real process in a Siemens W501D gas turbine (Electric power plant in Tula, Mexico) was presented in the study. A simple thermodynamic model was developed from the measured parameters to simulate the cycle performance. Architecture of ANN was 10 neurons in input layer, 12 neurons in one hidden layer and 4 neurons in output layer [21]. A general mathematical formulation based in ANN and ANNi aimed to optimize the performance of compressor was implemented. Nelder-Mead simplex method was applied to solve ANNi equation and to estimate the inlet optimum condition for a given compressor efficiency.

A set of experimental measured parameters were available by Cortes et al. [19]: $P_{amb} = 590$ mmHg, $T_{amb} = 30$ °C, $T_{wb} = 20$ °C, $\Delta P_{filter} = 6$ mmHg, $T_2 = 410$ °C, $P_2 = 10$ bar, $W_{NTG} = 59.29$ MW, $T_4 = 850$ K, $\dot{m}_f = 11817.54$ kg/h, $\eta_c = 80.68$, ΔT_{cooler} is supposed to be unknown.

The outcome value using ANNi methodology was $\Delta T_{cooler} = 4.9999$ °C. The numerical results for the calculation of the ΔT_{cooler}, for this case with ANNi strategy, had a discrepancy minor to 3.49×10^{-12}% with regard to thermodynamic model results ($\Delta T_{cooler} = 5$ °C). Different cases of validation and application of ANNi for optimization compressor performance were described using different operating conditions.

8. Conclusion

ANNi tool is an essential element to calculate the optimal operating conditions in the polygeneration processes. In this case, three examples of ANNi have been presented to simulate performance from developed artificial neural networks models. It is possible to calculate the optimum input parameter with the ANNi and considering the Nelder-Mead Simplex Method of optimization. In this paper, Nelder Mead Simplex is tested for a single parameter. Thanks to this methodology, it is possible to find any unknown input variable on-line in the different energy engineering processes. Through this, flexibility appears to be one of the main characteristics of ANNi system, enhancing its great interest as a tool for energy-engineering processes as it could be applied to other polygeneration systems.

Indeed, it is very important to note that the elapsed time to calculate the optimum input parameter is only a few seconds; thus, it is feasible to get optimal parameters on-line. In fact, the great advantages of using ANNi methodology are its speed and ease in predicting optimal parameters to control the engineering process. Furthermore, another advantage of ANNi strategy lays on the potentiality of extending it to other different processes and even to apply it to more industrial processes as to the energy systems.

It is important to note that if a neural network is going to be constructed with only one neuron in the hidden layer, then it would be not necessary to use the Nelder-Nead optimization method for the ANNi, because an analytical solution can be carried out. Nevertheless, if the neural network contains more than one neuron in the hidden layer, an optimization method would be required. Another thing to take into account is that the elapsed time to calculate the optimum parameter or parameters depends of the input, output and adjusted coefficient numbers.

If there are many input parameters to be found (solution to multi-parameter problems) then Nelder Mead Simplex wouldn't be capable of solving the optimization problem, it will be recommended to use another advanced techniques for optimization, such as: genetic algorithms and particle swarm optimization.

Nomenclature

AB	absorber
$b1$, $b2$	bias
CO	condenser
COP	coefficient of performance (dimensionless)
Ec	economizer
EV	evaporator
GE	generator
h	enthalpy (J/kg)
I	irreversibility (W) or electric current (amperes)
In	input value
K	number of neurons in the output layer
LW, IW	matrix weights
$\dot{m}$	mass flow (kg/s)
$\dot{m}_f$	fuel mass flow (kg/s)
n_s, n	neurons in the hidden layer
P	pressure (bar)
p	input
R	number of neurons in the input layer
S	number of neurons in the hidden layer
T	temperature [°C]
W_{NTG}	gas turbine net power (MW)
y	output value

Sub-index

Amb	ambient
ANN	artificial neural networks
ANNi	artificial neural network inverse
EXP	experimental
IN	input
wb	web bulb

Greek symbols

η	efficiency of compressor

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