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Exergetic Modelling of a 30-kW Gas Microturbine and Cogeneration System by Artificial Neural Networks

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Cogeneration systems with microturbine allow recuperating the low-quality energy that is normally wasted in conventional power generation systems. The aim of this article is to evaluate a cogeneration system using a Capstone 30-kW gas microturbine, to estimate the second law efficiency by training a backpropagation neural network using a thermodynamic model developed in HYSYS®, and to assess the performance indicators using Matlab®. The results show that the highest exergy destruction rate is in the combustion chamber, followed by the compressor and the heat recovery stage in the steam generator. From the parametric analysis it can be inferred that increasing the compression ratio, the isentropic compressor efficiency and the isentropic expander efficiency of the gas microturbine improves the overall thermodynamic system performance. In addition, the outlet temperature of the preheater significantly affects the thermal and exergoeconomic system performance. However, only parameters that present good performance and can be improved for prediction purposes were considered in neural network training.

1. Introduction

Energy is the fundamental motor of sustainable development in society. The guarantee of access to sustainable energy systems, with the use of modern fuels, is closely linked to the development goals of global organisations, such as the United Nations (Nakata et al., 2011). Electric power generation systems through thermal power plants play a fundamental role in the industrial activity of a country, seeking to satisfy the needs of human development that allows better living conditions for a society (Sonar et al., 2014). Approximately 80% of the energy obtained in thermal power plants comes from fossil fuels, while only 20% of electricity is obtained from different sources, such as hydro, nuclear, wind, and solar (Erdem et al., 2009).
Numerous studies have been undertaken to maximise exergy and energy efficiency from various energy generation alternatives including the study of cogeneration and trigeneration plants to reduce the environmental impact at the lowest possible cost (Ahmadi et al., 2011). One of the most widely used alternatives in small-scale power generation is the gas microturbine, which operates under the Bryton thermodynamic cycle. Its goal is to transform the chemical energy of the fuel into mechanical work in a gas turbine that normally operates in cogeneration, where electricity is simultaneously produced with heat recovery. This transformation process removes energy in the form of heat and an exergy destruction process that affects the energy efficiency of the plant (Çengel and Ghajar, 2011). In addition, there are trigeneration systems that simultaneously produce cold, heat, and electricity from familiar energy sources (Ahmadi et al., 2011).
Various energetic and exegetic studies have been conducted in thermal generation systems (Anvari et al., 2015) These studies allowed the thermodynamical characterisation of the system and identified potential opportunities for plant improvement (Suamir et al., 2012). Numerous studies have also been conducted on control and monitoring systems based on artificial neural networks, genetic algorithms, diffuse logic, and artificial intelligence for power generation, cogeneration, and trigeneration plants (Sonar et al., 2014). Reddy and Mohammed (2007)

conducted a parametric study to determine the effect of gas turbine inlet temperature and pressure ratios on the exergetic efficiency of combined cycles. Datta et al. (2010) energetic and exergetic analysis was presented for a gas turbine coupled with a biomass gasifier to use a set of specific parameters for thermal studies under three different configurations, in which the variations of the first and second law efficiencies were established for three different cases. Woudstra et al. (2010) determined the generation levels for a cogeneration process to reduce heat and exergy losses due to exhaust gases.

Sisworahardjo et al. (2008) introduced an artificial neural network control for gas turbine power generation plants to monitor and control the plant through proportional derivative controllers and artificial neural networks (ANN). Bartolini et al. (2011) developed a significant contribution by training two ANN models for monitoring and controlling a boiler and a steam turbine, which were then integrated general plant control. Nikpey et al. (2014) developed an application of neural network models for monitoring the performance of similar devices for three different applications including covering performance diagrams, environmental parameters, and pollutant emissions.

The present study uses Aspen Hysys® and Matlab® to simulate a 30-kW Gas Microturbine and Cogeneration System, with the aim of generating enough input-output data to train an ANN model. This model was used to measure the influence of input variables, such as isoentropic efficiency of the turbine, isoentropic efficiency of the compressor, air inlet temperature, and air-fuel flow ratio in the combustion chamber, on output variables, such as efficiency of the first and second law of thermodynamics in the plant and the destruction of exergy.

2. Methodology

This section explains the cogeneration process with its respective operating conditions including the theoretical foundations of the energy and exergy balances, the equations used to calculate the exergies of mixed gases and gases, the destruction rate, indices of exergy losses, and basic concepts of neural networks by error backpropagation.

2.1 Process description

Cogeneration systems are commonly used in power generation plants. They allow the use of residual energy from a fluid that is not converted into electrical energy to feed thermal processes, such as steam generation. Figure 1 shows a cogeneration system model for electricity and steam generation, which includes a compressor that is coupled with the turbine shaft to transmit the power to carry out the compression work, an air preheater, a combustion chamber, the expansion stage, where the combustion gases transform their energy into rotational mechanical work, and a heat transfer in the steam generator to recover the exhaust gas energy and produce steam for various processes, depending on the intended use of the system.

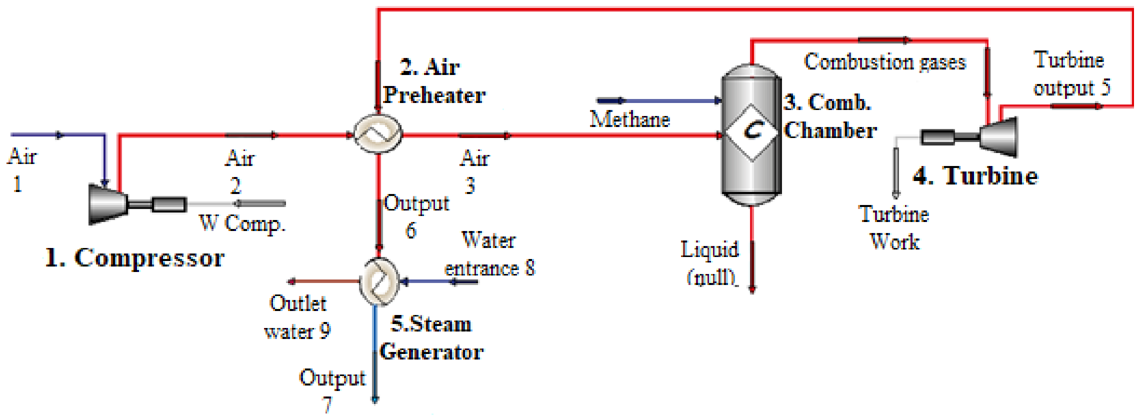

Figure 1: Diagram of the Cogeneration Plant.

In this study, the air was considered with a composition of 78.98 % N_2, 20.99 % O_2, 0.03 % CO_2, using the Peng-Robinson state equation and assuming a complete combustion of methane resulting in the thermodynamic states for the 30 kW microturbine of, as shown in Table 1. The obtained results in terms of mass flow, pressure, temperature, enthalpy, and entropy allowed the estimation of the exergy of the systems and its second law efficiency.

Table 1. Thermodynamic properties of microturbine cycle.

State	Substance	$\dot{m}\left({}^{kg}/_{s}\right)$	$P(kPa)$	$T(°C)$	$h\left({}^{kJ}/_{kmol}\right)$	$s\left({}^{kJ}/_{Kmol*K}\right)$
1	Air	0.304	101.3	30	-52.65	152.2
2	Air	0.304	364.7	190.4	4,935	154.7
3	Air	0.304	361.7	400	11,170	165.7
4	P. combustion	0.306	361.7	681.1	10,160	179.3
5	P. combustion	0.306	108.5	472.2	2,824	181.4
6	P. combustion	0.306	105.5	269.7	-3,342	171.9
7	P. combustion	0.306	102.5	162	-6,355	165.9
8	Water	0.016	101	30	-285,800	55
9	Water (Vapour)	0.016	98	100	-25,1100	150
10	Natural Gas	0.002	370	25	-75,330	171.4

2.2 Theoretical basis

The mass, energy, and entropy are properties that can be transferred into or out of the open systems. Exergy is an extensive property and its balance is presented in Equation (1) (Çengel and Ghajar, 2011)

$$\frac{dE_{cv}}{dt} = \sum_{j}\left(1-\frac{T_o}{T_j}\right)\dot{Q}_j - \left(\dot{W}_{cv} - p_o\frac{dV_{cv}}{dt}\right) + \sum_{e}\dot{m}_e e_e - \sum_{s}\dot{m}_s e_s - \dot{E}_D \tag{1}$$

where $\frac{dE_{cv}}{dt}$ is the rate of exergy variation, T_o and T_j are the reference boundary temperatures respectively. The energy rate transfer by heat and work are expressed by $\dot{Q}$ and $\dot{W}$, while e is the exergy associated with the mass flow into or out of the control volume, which is the maximum theoretical work that can be obtained and is expressed by Eq(2)

$$e = e^{PH} + \frac{1}{2}V^2 + gz + e^{CH}, \qquad E^{PH} = (h-h_0) - T_0(S-S_0) \tag{2}$$

where e^{PH} is the physical component of the exergy transference associated with the temperature and pressure of the mass flow, and is calculated employing Eq(3)

$$e^{PH} = (h-h_o) - T_o(s-s_o) \tag{3}$$

The chemical exergy of mixed gases such as O_2, N_2, CO_2 and, H_2O is given by Eq(4)

$$e_k^{-CH} = \sum x_k e_k^{-CH} + \bar{R}T_0 \sum x_k \ln x_k \tag{4}$$

where the gas phase is at a temperature T_0, and x_k^e is the molar fraction of gas k.**T**he rate of exergy destruction in a system component ($\dot{E}_D$) can be divided by the fuel exergy rate provided to the same system ($\dot{E}_{C,tot}$) obtaining the decay rate y_D from Eq(5)

$$y^*{}_D = \frac{\dot{E}_D}{\dot{E}_{C,tot}} \tag{5}$$

The calculation of exergetic efficiency is shown in Eq(6).

$$e = \frac{W_{net} + (\dot{E}_{e\,(Water)} - \dot{E}_{in\,(Water)})}{\dot{E}_{in\,(Fuel)} + \dot{E}_{in\,(Air)}} \tag{6}$$

2.3 Neutral network for error backpropagation

Backpropagation algorithm is shown from Eq(7) to Eq(11). It has been widely used to predict the thermodynamic behaviour of processes (Rossi et al., 2014). The input data structure of the neural network is described starting from Eq(7).

$$\vec{y}_0 = \vec{x} \tag{7}$$

Subsequently, the recursive calculation is spread forward to $l = 1,2,...,L$, as shown in Eq(8)

$$\vec{y}_l = f_l(W_l \cdot \vec{y}_{l-1} + \vec{b}_l) \quad (8)$$

where W_l is the weight deviation vector. The error estimation in the output structure is calculated using Eq(9), whereas the backpropagation of the error to $l = L-1, L-2, ..., 1$ is calculated using Eq(10).

$$\vec{\delta}_L = \vec{t} - \vec{y}_L \quad (9)$$

$$\vec{\delta}_l = \left(W_{l+1}^T \cdot \vec{\delta}_{l+1}\right) \cdot f_l'\left(\overrightarrow{net}_l\right) \quad (10)$$

where the super index T is the transposed matrix operator. The weights are updated using Eq (11), which is given as follows.

$$\Delta W_l = \vec{\delta}_l \vec{y}_{l-1}^T \quad (11)$$

3. Results and discussions

3.1 Destruction and exergy loss rates

In the system simulation, a case study is carried out by varying the air flow at the compressor inlet allowing the change of air-to-fuel for a constant fuel flow (Methane) of 7.2 kg/h (0.002 kg/s). From this parametric study, the exergetic properties and destructions were calculated for the system components and global system. Figure 2 shows the exergy destruction variations for each element of the system with different pressure ratios in the compressor (Rc), which shows a direct proportional behaviour between the air-fuel ratio and the exergy destruction of the compressor and the turbine. Similar condition is considered for the Rc variation.

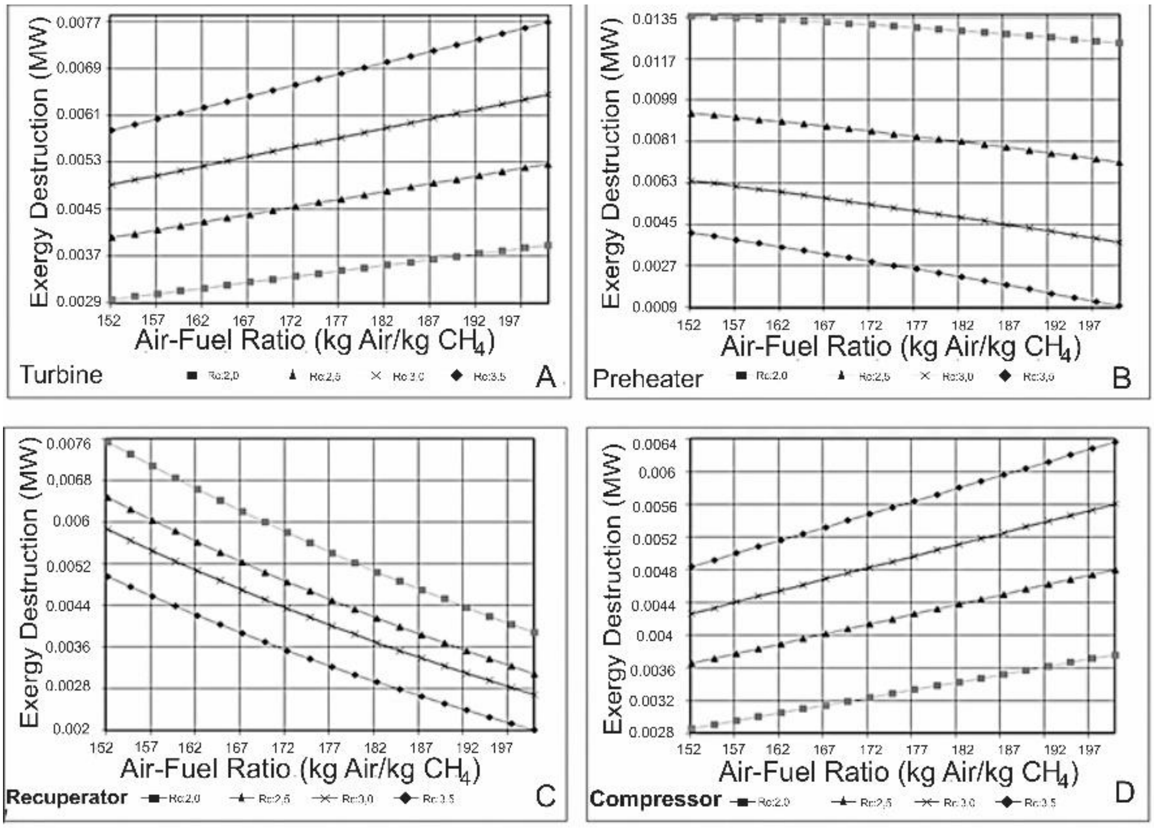

Figure 2: Exergy destruction in each component of the system under different pressure conditions in the a) turbine, b) preheater, c) recuperator, and d) compressor.

3.2 Training and validation of the neural network

To train the ANN model by backpropagation to estimate the second law of thermodynamics efficiency, 100,700 data were obtained from the Aspen Hysys® and Matlab® simulation. Data such as the compressor efficiency, turbine efficiency, and input air temperature, were collected while keeping the fuel-air ratio fixed. The results show an average quadratic error of 0.0137 for 23 iterations for ten layers, 15 neurons per layer, and 0.5 of learning constant. Figure 3 shows the behaviour of the mean square error as a function of iterations for network training.

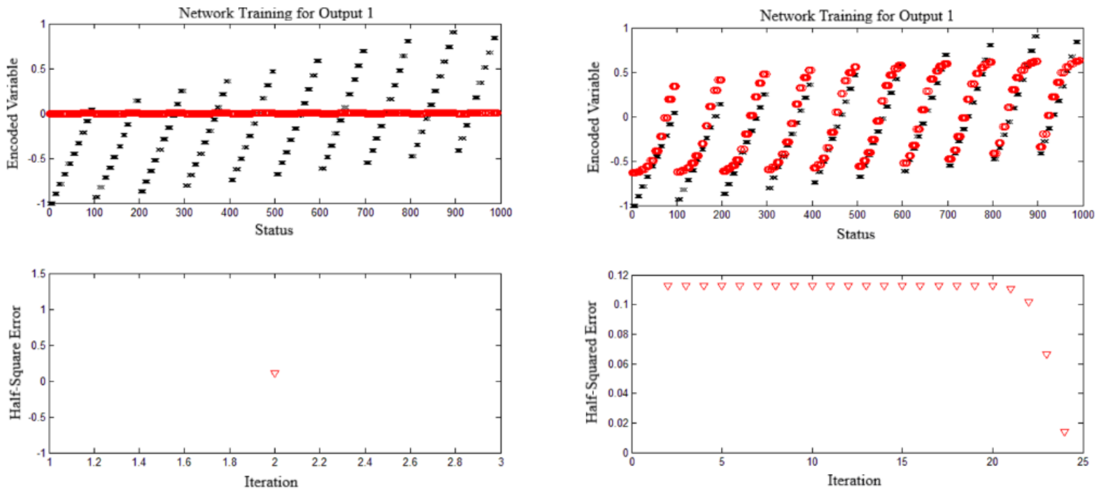

Figure 3: Mean squared error behaviour depending on the iterations in training network.

To validate the capacity of the network to predict the second law efficiency, a new set of 300 system operating conditions were simulated under a fixed fuel-air ratio of 100, air temperatures ranging from 15°C to 35°C, and compressor and turbine efficiencies ranging from 70 % to 87 %. The ANN model was then tested to assess its prediction capacity showing an average quadratic error of 0.1152, which indicates a good performance of the algorithm implemented as shown in Figure 4, where the second law efficiency prediction of the neural network is compared to the real system data.

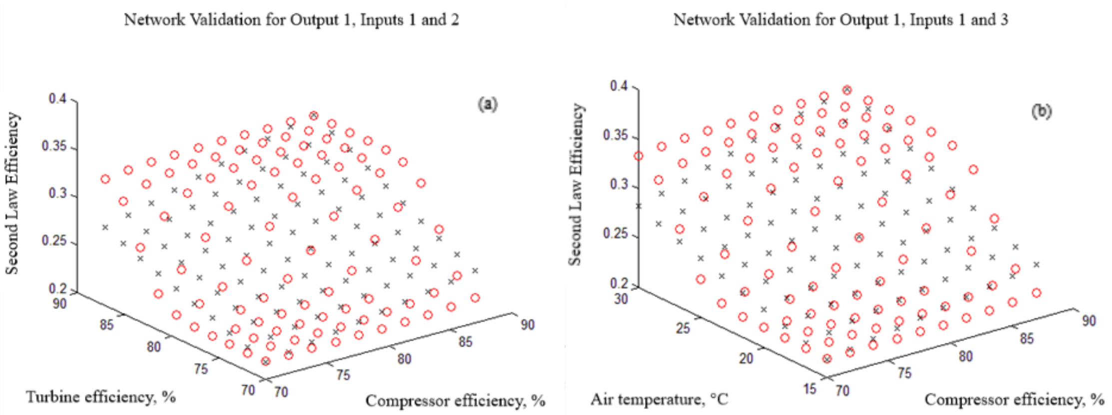

Figure 4: Prediction of the efficiency of the second law (output 1) of the neural network versus actual system data; a) efficiency of the turbine (input 1) and compressor (data 2) and b) efficiency of the compressor and air temperature (input 3).

When the network topology for this process has been determined, with more than 20 layers and 30 neurons per layer assigned, the network is over-parametered. Since the adjustment error in the training datasets tends to be reduced to zero, the network's ability to predict output data on new inputs is significantly reduced, especially when the input data is outside the training range.

4. Conclusions

The results of the parametric studies revealed that the increase in compression ratio, the isentropic efficiency of the compressor, and the expansion stage improved the thermodynamic performance of the gas microturbine. However, it is important to consider variables, such as air input temperature, which significantly affects the exergetic efficiency of the process. An a priori analysis of output sensitivity with respect to the inputs and their implications is not necessary when applying neural networks to predict the efficiency of the second law of microturbine. However, in cases where the fuel-air/temperature ratio at the output of the super heater is considered, the network loses the ability to make predictions with acceptable accuracy and to achieve an acceptable mean quadratic error at the process stage. In conclusion, neural networks are an excellent alternative for a prediction method for this type of power generation systems. Studies on activation function, network type, number of layers, number of neurons, and constant learning are required for further improvement.

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