THERMODYNAMIC DIAGNOSTIC METHODOLOGY USING THERMOECONOMIC AND THERMODYNAMIC INDICATORS IN CONJUNCTION WITH ARTIFICIAL NEURAL NETWORKS (ANN)

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Abstract. *For decades several methodologies had been developed with the aim to solve the main problem of the thermodynamic diagnosis (TD), that is, identify which equipment has malfunctions and quantify in terms of additional fuel consumption such malfunctions. TD has two trends: one based on thermoeconomic indicators (exergetic cost) and another based on thermodynamic indicators (pressure, temperature, mass flow, etc.). However these methods often only achieve their objective partially, so sometimes it is necessary to use two or more of these methods together. In this paper a diagnostic methodology was developed for externally fired gas turbines (EFGT) using the thermoeconomic method in conjunction with artificial neural networks to identify not only components with malfunctions (intrinsic malfunctions) and their fuel impact, but also the fuel impact of the thermodynamic parameters (for example, fuel impact of temperature variation). An EFGT was simulated using the commercial software GateCycleTM using wood carbonization residual gas as fuel. An artificial neuronal network (ANN) was developed with the commercial software MATLAB®. To show the applicability of the methodology is considered 5% of degradation in the performance of the Compressor and the Burner. Under these conditions are obtained intrinsic malfunctions of 15,405kW and 5.11 kW in the burner and the compressor, respectively, where, the intrinsic malfunction of 5.11 kW in the compressor is represented by 8.6572 kW caused by a greater consumption of shaft work and -3.5474 kW caused by the compressor exit temperature. In the Burner the intrinsic malfunction of 15,405 kW is caused by the combustion temperature.*

Keywords*: artificial neuronal network, externally fired gas turbine, fuel impact, intrinsic malfunction, thermodynamic diagnosis*

1. INTRODUCTION

The thermoeconomic diagnosis (TED) appears as a tool to identify energy system's components with malfunctions and to quantify the proportion in which the degradation of a component is responsible for the an additional fuel consumption for a given system (Valero, Correas, Zaleta, et al. 2004b). The malfunctions can cause that a system needs more fuel for each unit produced, representing a reduction in system efficiency (Pacheco et al., 2007). Several methodologies have been developed over various decades to solve the problem of diagnosis, but often without achieving completely their goal or reaching it partially due to that feature the various limitations. For example, there are methods that manage to identify the component with malfunctions, but cannot calculate its fuel impact (Royo et al., 1997; Toffolo and Lazzaretto, 2004). Others fail in the presence of more than one intrinsic malfunction (Zaleta et al., 1998; Reini and Taccani, 2004) or cannot separate the intrinsic malfunction of induced malfunction (Valero et al., 1999; Torres et al., 2002; Verda, 2006). There are methods where the diagnosis result is reported as the fuel impact of the diagnosis parameters, but without establishing if these parameter variations are due to intrinsic or induced malfunctions (Remiro and Lozano, 2007; Correas et al., 1999). There are methods that allow identifying the equipment with intrinsic degradation, but require to know beforehand the malfunctions (or to simulate all the intrinsic malfunctions that could happen). Then, it is necessary to know beforehand the effects of the degradations over the performance parameters, what at first is something without sense, because the objective of the diagnosis is to discover the malfunctions (Verda, 2006; Tsalavoutas et al., 2000; Verda et al., 2004; Verda et al., 2002; Verda et al., 2001). Thus, is it reasonable to diagnose if the malfunction are already known? (Orozco et al., 2016). In this work, thermoeconomic diagnostic methodology based on Fuel Impact Formula was applied to an externally fired gas turbine (EFGT), but using the variant proposed by Rúa et al. (2013) and Orozco et al. (2016). These authors proposed a methodology that integrates the diagnostic methods based on thermoeconomic indicators with thermodynamic parameters. The EFGT cycle was simulated using the commercial software GateCycleTM 5.51 for various operating conditions: a reference condition (no degradation) and test condition (with malfunctions). Artificial Neural Networks (ANN) were used for simulated the system's components outputs on off-design condition without malfunctions.

2. THERMOECONOMIC DIAGNOSIS AND FUEL IMPACT FORMULA

According to Pacheco (2011), the fuel impact formula presented in Eq.(1) is very important for diagnosis because relates the variation of fuel consumption (ΔF_T) of a system with the unit exergetic consumption variation ($\Delta\langle KP\rangle$) of the system components and the production variation (ΔP_S). This equation was suggested by Valero et al. (1990) and Valero et al. (1999) and was developed by Torres et al. (1999), Lazzaretto and Toffolo (2006) and Valero et al. (2004a).

$$\Delta F_T = \left(\Delta^t \kappa_e + {}^t k_P^*(x)\Delta\langle KP\rangle\right)P(x_0) + k_P^{*t}\Delta P_S \quad \textbf{(1)}$$

Where the term $\Delta^t \kappa_e P(x_0)$ is the fuel impact due to the variation of the unit exergetic consumption; ${}^t k_P^*(x)\Delta\langle KP\rangle P(x_0)$ is the fuel impact due to o the variation of the unit exergetic consumption of the resources of the components because a malfunction. and $k_P^{*t}\Delta P_S$ the fuel impact as a consequence of the variation of the total product of the system (Pacheco ,2011). When the unit exergetic consumption ($\Delta\kappa_{ji}$) of a component increases the irreversibility of this component also increases in an amount that is called of **malfunction (*MF*)** (Eq. (2)),(Toffolo and Lazzaretto, 2004; Reini and Taccani, 2004; Valero et al., 2004a; Verda et al., 2003; Zaleta et al., 2004).

$$MFi = \Delta\kappa_i P_i(x_0) \quad (2)$$

There are two types of malfunctions. When the unit exergetic consumption of a component increases due to degradation in the component itself is called **intrinsic malfunction**. When an intrinsic malfunction occurs, the operation points of the other components change. Thus, variations in the specific consumption of the other components appear, which leads to **induced malfunction** (caused by the variation of input). Since the problem of induced malfunction is the main difficulty in the application of the fuel impact formula for diagnosis of energy systems, several methods have been developed to treat it. and its support could be consulted in Valero et al. (2004b), Toffolo and Lazzaretto (2004), Reini and Taccani (2004), Valero et al. (2004a), Verda et al. (2003), Zaleta et al. (2004); Verda (2004), Correas (2004), Valero et al. (2004) and Lazzaretto et al. (2006). The irreversibility of a component can also vary due to a change in its product. This is called **dysfunction (*DF*)** and is determined by (Eq. (3)):

$$DFi = \left(\kappa_i(x) - 1\right)\Delta P_i \quad (3)$$

Several authors more interested in implementing the thermoeconomic diagnosis in current operating systems propose the use of methods based on the Thermodynamic description using variables that are widely accepted in industrial practice such as: pressure, temperature and efficiencies (Usón et al., 2010), losing the homogeneity of the parameters (each parameter has a different unit of measure). In thermoeconomic methods all material (mass) and energy flows are described using exergy and, therefore quantified in energy units (Usón and Valero, 2011). In this work it is used the thermoeconomic approach, where all flows are expressed in terms of exergy, to develop a thermodynamic diagnosis methodology for an externally fired gas turbine cycle (EFGT) using the fuel impact formula, but with a modification that allows to identify the equipment with intrinsic malfunctions, even when it has various degraded components. The methodology that was proposed by Rúa et al. (2013) and Orozco et al. (2016) is expanded here to take into account the impact of variation in the fuel parameters, such as pressure and temperature caused by malfunctions.

3. DESCRIPTION OF THE EFGT CYCLE

For this work was simulated an externally fired gas turbine (EFGT) using commercial software GateCycle™ (Gate Cycle, 2003). For the design point were used data adopted by Kautz and Hansen (2007) with some modifications to achieve a net power of 99,80 kW using wood carbonization residual gas as fuel, with the following chemical composition in mass fraction (dry base): H_2(0,63%); CO(34%); CO_2(62%); CH_4(2,43%); C_2H_6(0,13%) and other gases (0,81%) (Vilela et al., 2014). The model is used to analyze the effects caused by malfunctions in the cycle components over the fuel consumption. The EFGT cycle (Fig. 1) is composed by a compressor, a turbine (expander), a heat exchanger and a burner, where the fuel is externally burned. Air at environmental conditions (1) enters the compressor where it is compressed to a pressure of 4.5 times the atmospheric pressure, reaching a temperature of 214ºC, immediately the gas enters the heat exchanger, where is heated by the combustion of the gases from residual carbonization of the wood that is happening in the burner (5). The hot gases leave the exchanger (3) and are expanded in the turbine. The gases leaving the turbine (4) are used in the burner to improve the efficiency of the cycle. Finally, the combustion gases, after rendering their heat to the air at the heat exchanger, is discharger to the atmosphere (6). The input of fuel in Figure 1, correspond to the flow 7. More information about EFGT systems could be consulted in Kautz and Hansen (2007), Al-attab & Zainal (2015), Baina et al. (2015) and Cocco et al. (2006).

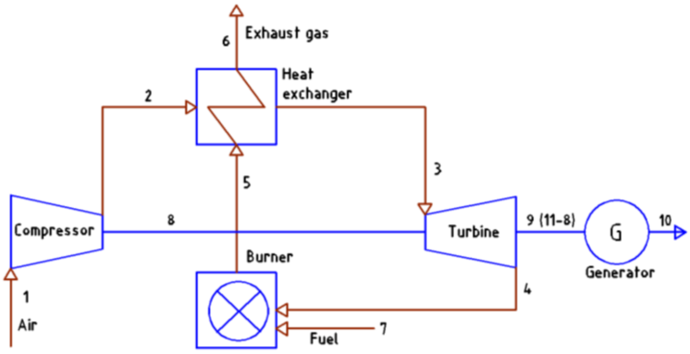

Figure. 1. Externally fired gas turbine. Adapted from (Kautz and Hansen, 2007)

Table 1 shows the main parameters of the EFGT cycle (design point) used in the model developed in this study. All the calculations for the design point were done using ISO conditions (15 ºC/ 101 kPa / 60% humidity) and disregarding pressure drop in the component's connection pipes, heat exchanger, and burner.

Table 1. Design point data for the EFGT system

Parameter	**Value**	**Unit**	**Parameter**	**Value**	**Unit**
Net power	99.8	kW	Air mass flow (m_1)	0.8	kg/s
Turbine power	268	kW	Fuel mass flow (m_7)	0.071	kg/s
Compressor power	162	kW	Combustion gases mass flow (m_5)	0.871	kg/s
Efficiency, ISO	25.68	%	Exhaust gas temperature (T_6)	329	°C
Fuel input temperature	60	°C	Combustion gases temperature (T_5)	900	°C
PCI of the fuel	5470	kJ/kg	Pressure ratio	4.5	
Air temperature at the output of the compressor (T_2)	214	°C	Compressor Efficiency	76.8	%
Air temperature at the turbine input (T_3)	850	°C	Turbine Efficiency	82.6	%
Air temperature at the turbine output (T_4)	557	°C	Heat exchanger area	164	m²

4. INTRINSIC MALFUNCTIONS IN THERMAL SYSTEM COMPONENTS

Consider the hypothetical cycle shown in Fig. 2a. Individual models of equipment (A, B and C) were created (Fig. 2b). The outputs of both the equipment of the thermodynamic cycle (Fig. 2a) as the individual equipment (Fig.2b) must be equal for the same inputs in the reference condition.

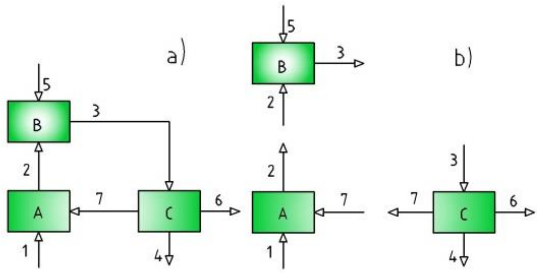

Figure. 2. a) Basic thermal cycle in the reference condition. b) Individual models of the equipments of the basic thermal cycle in the reference condition.

Now, the original model is taken to a test condition where the components work off design (Fig. 3a). Moreover, the equipment "A" presents an intrinsic malfunction. In this new condition the cycle flows change their values (1→1'), (2→2'), (3→3'), etc. (Rúa et al. 2013). If these new values are used as inputs of the individual models (without intrinsic malfunctions) the output values of the devices "B" and "C" are equal for both the original cycle (test condition) as for the corresponding individual model (Fig. 3b). However, for equipment "A" (which has intrinsic malfunction in test condition) outputs are different (2'≠ 2'') (Rúa et al. 2013).

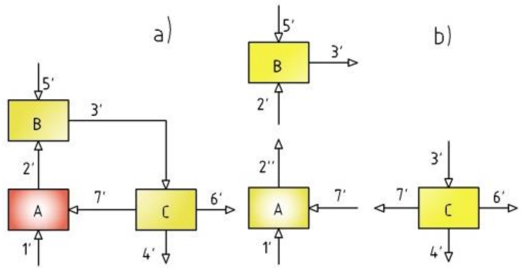

Figure. 3. a) Basic thermal cycle at current condition with intrinsic malfunction in equipment A. b) Individual models of the equipments of the basic thermal cycle with the same inputs of the basic thermal cycle at the current condition.

For the device "A" the presence of a malfunction is equivalent to having a fictitious component that modifies device outputs according to the magnitude of degradation. Thus, device "A" within a thermal cycle could be represented by two components (Fig. 4): the first component is the equipment without anomalies (A*) but working off design and the second component (D) is the effects of malfunction over the output stream of the device A*.

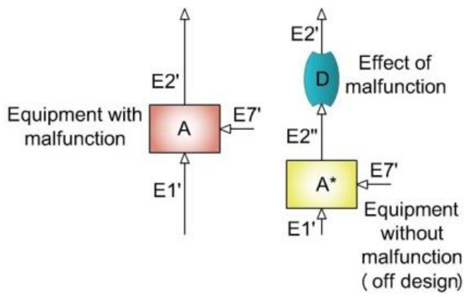

Figure. 4. Disaggregation of the malfunction over the output of the equipment A under the current condition. Adapted from (Rúa et al. 2013).

This type of element "D" is called Exergetic Operator (EO) (Orozco et al., 2016). From historical data or from simulation an ANN is created, which represent the behavior of equipment "A" without malfunctions (A*) for different operation conditions. In the same way, if inputs of equipment "A" (E1' and E7') are used as inputs of equipment A*, the output E2" is obtained. At entering the flow E2" in EO is affected by the presence of the malfunction of equipment A, having as output the flow E2', which represent the value of the exergy of the equipment "A" at the current condition.

An artificial neural network (ANN) is an interconnection of computing elements known as neurons that has only three sets of rules: multiplication, sum and activation. As shown in Eq. (4) (Usón and Valero, 2010) each input value ($\boldsymbol{p}$) is weighted, i.e. multiplied by its corresponding weight ($\boldsymbol{W}$). Then add up all the weighted inputs and bias (b). The result of this sum goes through an activation function also called transfer function to thereby obtain the neuron output (a). In general, neural networks are tools for building systems models that are characterized by sets of data that are often (but not always) obtained by sampling a system input-output behavior (Tosh and Ruxton, 2010). More information about the ANN, their topologies and learning algorithms could be consulted in the work of Suzuki (2011), Tosh and Ruxton (2010), Vankayala and Rao (1993), Suzuki (2013), Fast and Palmé (2010) and Kalogirou (2001). To simulate the behavior of individual equipment without malfunctions and working off design was used the tool "*nntool*" of the commercial softwarel Matlab®. The neural network used was the type "*feed-forward backprop*" with a hidden layer and a transfer function "*tansig*". The number of neurons in the hidden layer depends on the number of inputs and outputs of the network which in turn depends on the characteristics of the simulated equipment. A network for each device was created. Several simulations of the EFGT model in GateCycle were made by varying different parameters and operating conditions. The data obtained from these simulations were used then to train the ANN in each individual component.

$$a = f(\boldsymbol{W} \cdot \boldsymbol{p} + b) \quad (4)$$

5. RESULTS

By using the concept of "exergetic Operator (EO)" for EFGT cycle, a modified physical structure called "transition structure" is created. The transition structure (TE) is shown in Fig. 5a.

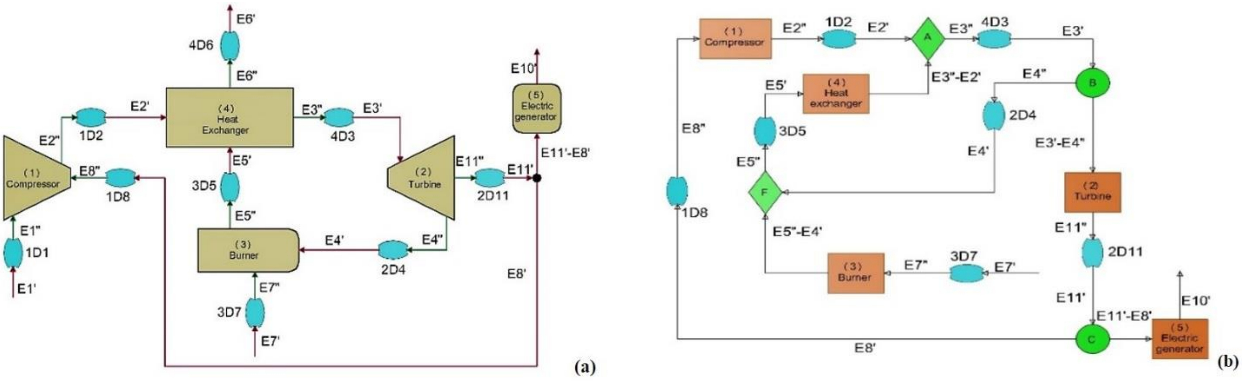

Fig. 5. a) Transition structure for the EFGT cycle. b) Productive structure of the EFGT cycle, based on the TE.

The effect of malfunction (EO) is symbolized as xDy where "x" is the equipment in which is produced the malfunction and "y" represents the output stream that is changed because of the malfunction. Thus for example, the Exergetic operator 3D5 mean malfunction in the equipment 3 (in our case the burner) which changes the value of the output stream 5.

From the transition structure of Fig. 5a is elaborated the productive structure, as shown in Fig. 5b, which will be used to apply the methodology of fuel impact. To test the methodology described above, it is considered that the compressor and the burner have intrinsic malfunctions (current condition). For the purposes of malfunctions, the performance factor (GateCycle model) was multiplied by 0.95 for both the compressor and to the burner, which is considered a 5% degradation in the performance of the corresponding equipment. With the data-inputs of each device in the current condition, ANN was simulated thereby obtaining the outputs of the individual devices.

Table 2 shows the exergy values of each stream in the reference condition, current condition (GateCycle) and the individual models (ANN). Table 3 presents the thermoeconomic diagnosis results for the condition: malfunctions in compressor and burner.

Table 2. Flow of the exergy for the productive structure of Fig. 5

Stream	Reference condition (E)	Current condition (E')	Individual Models (E")	EP'	EP'T'
1	0	0	0	0	0
2	138.97	148.36	144.57	144.57	148.36
3	490.64	521.31	521.31	521.31	521.31
4	202.10	216.06	216.06	216.06	216.06
5	470.12	505.89	522.46	522.46	505.89
6	92.11	105.82	105.82	105.82	105.82
7	360.84	439.76	439.76	439.76	439.76
8	162.33	177.65	168.66	-	-
9*	105.70	106.42	106.42	-	-
10	99.81	100.02	100.02	-	-
11**	268.03	284.07	284.02	-	-

* The stream 9 is the difference between the flows 11 and 8; ** The stream 11 is the total shaft work of the turbine

Thus in Table 3, the malfunctions that appear in the system's components: compressor, turbine, burner, heat exchanger and electric generator are malfunctions of the induced type because the calculation of them was made considering the outputs obtained from the individual models (without intrinsic malfunctions). In this way, the intrinsic malfunctions of the EFGT cycle's components are represented by the EO, that correspond to each equipment.

Table 3. Results of the thermoeconomic diagnosis of the EFGT cycle.

Equip.	Description	MF (kW)	DF (kW)	Equip.	Description	MF (kW)	DF (kW)
1	Compressor	-0.2024	-0.6786	F	Junction (burner)	5.24E-14	-18.5731
2	Turbine	-0.4859	-1.3826	1D2	EO	-3.5474	-14.466
3	Burner	-4.1326	0	1D8	EO	8.6572	27.1175
4	Heat exchanger	6.8817	10.403	2D4	EO	0	0
5	Electric generator	0.4946	1.5492	2D11	EO	-0.0472	-0.148
A	Junction (heat exchanger)	-2.72E-14	1.017	3D5	EO	15.405	22.06
B	Branch (Turbine)	0	0	3D7	EO	0	0
C	Branch (electric generator)	-8.44E-07	-2.64E-06	4D3	EO	1.51E-05	4.30E-05

For example, the device 3 (burner) presents an induced malfunction of -4.1326 kW and an intrinsic malfunction (EO

3D5) of 15.405kW. In Figure 6 it can be observed the fuel impact for each equipment disaggregated into its three components (intrinsic malfunction, induced malfunction and dysfunction).

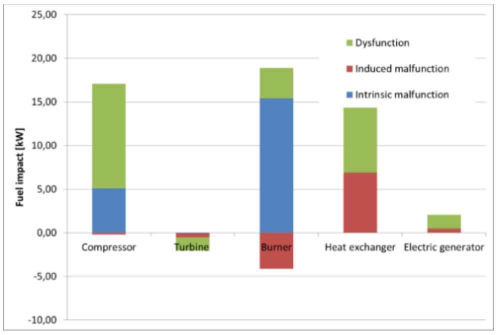

Figure 6. Malfunctions and dysfunctions of the components of the EFGT cycle

Therefore, the compressor has a fuel impact of 16.88 kW of which 5.11 kW are intrinsic malfunction, -0.202 kW are induced anomalies and 11.97 kW are dysfunctions. In turn, the burner also presents a dysfunction of 22.06 kW and impact on fuel 33.33 kW. The heat exchanger has an impact of 17.28 kW and the turbine has an impact of -2.063 kW.

For the fuel impact on the thermodynamic parameters (mass flow, temperature and pressure) the Exergetic Operators of the original transition structure are disaggregated into three sequential components (only EO associated with matter flows) called "Sub-EO". For example, the EO 1D2 can be decomposed into three Sub-EO: 1P2 (pressure effect), 1T2 (temperature effect) and 1M2 (mass effect). A new transition structure with its corresponding productive structure is shown in Fig. 7. The values of the flows EP' and EP'T' that appear in the last two columns of Tab. 2 and Fig. 7 are calculated using Eq. (5) and Eq. (6).

$$E_i^{P'} = f(P', T^{"}, m^{"}) \tag{5}$$

$$E_i^{P'T'} = f(P', T', m^{"}) \tag{6}$$

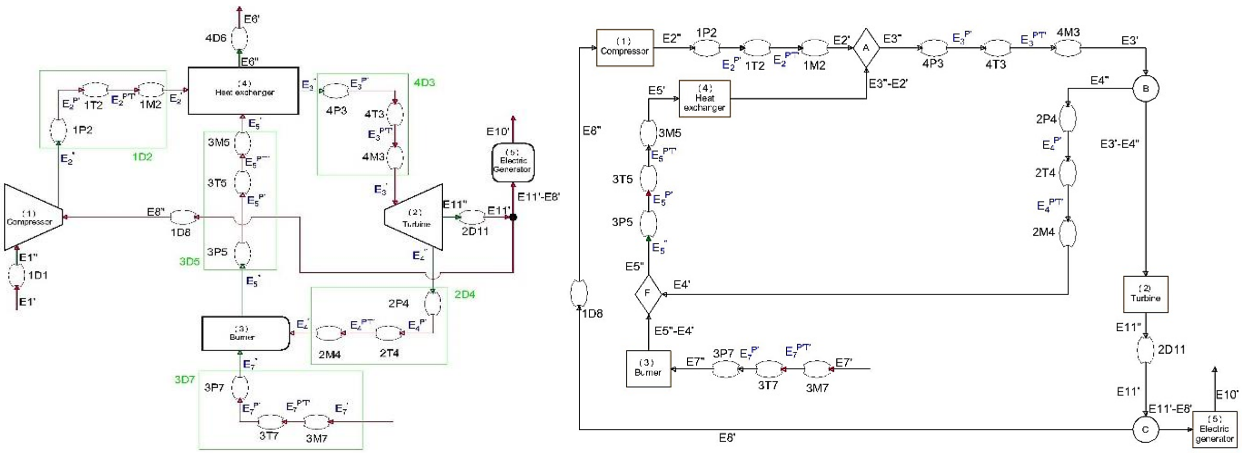

Figure 7. a) New TE for the EFGT cycle. b) Productive structure of the EFGT cycle, based on the new TE.

The result of diagnosis are presented in Tab. 4.

Table 4. Result of diagnosis based in the new Productive structure used Sub-EO

Device		*MF* (kW)	*DF* (kW)	Device		*MF* (kW)	*DF* (kW)
EO	Sub-EO			EO	Sub-EO		
1D2	1P2	0	0	4D3	4M3	0	0
	1T2	-3,5474	-14,466	3D7	3M7	0	0
	1M2	0	0		3T7	0	0
2D4	2P4	0	0		3P7	0	0
	2T4	0	0	3D5	3P5	0	0
	2M4	0	0		3T5	15,405	22,06
4D3	4P3	0	0		3M5	0	0
	4T3	1,51E-05	4,30E-05	-	-	-	-

In the Burner the intrinsic malfunction of 15,405 kW is caused by the combustion temperature. The aim of the diagnosis is obtained: the components with intrinsic malfunctions are identified and the fuel impact quantified. Also, the thermodynamic parameters that cause intrinsic malfunctions are identified.

6 CONCLUSIONS

One of the major limitations that the thermoeconomic diagnosis methodology present is that when there is more than one component with intrinsic malfunctions it is practically impossible to identify where the malfunctions are occurring. This is because while working with energy flows they cannot observe the changes that occur in pressures, temperatures and mass flows. This limitation can be solved using the Exergetic Operators methodology that identifies the equipment with intrinsic malfunctions. However, this methodology implies knowing the behavior (outputs) of each device for operating conditions (inputs) when they do not present malfunctions and work in off-design. A way to predict this behavior is to create and train artificial neural networks that simulate the performance of each individual equipment. This allows the methodology reached the desired results. By modifying the methodology, i.e., disaggregating OE in its sub-OE) is determined approximately the thermodynamic parameters that cause malfunctions.

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