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Analysis of Heat Transference in the Regenerative Exchanger of a Thermal Power Plant*

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The process of electricity generation in a power plant involves several phases for heat exchange generally between hot fluid (water, fumes or steam) and one of the input fluids (cool water, cook oven gas, fuel, blast furnace gas, etc.). The process of exchange evolves in time at the same time as installation itself. This work presents a study to create a model for a regenerative rotative heat exchanger that considers the effects of the time dependent variations. This improvement is another step in a deep study of the time-changing conditions of the heat transmission due to ageing, but it will also make possible the introduction of new parameters in the physical formulation whose relation is unknown. Modelling is done using feedforward neural networks after a very extensive pre-processing step.

Keywords: Data processing; Heat exchange; Modelling; Neural networks; Power plant

1. Introduction

The production of electricity from combustible materials is a very complex and changing process. From the basic idea (fuel is burnt to produce steam, which is used to move a turbine), the process is enriched with complementary processes to improve the global performance. However, the utilities do not work in a continuous regime, especially now that the market is liberalised and production is directly linked to sales.

Electricity generation is basically a heat transference process. The heat is transferred in several steps from one fluid to the other, involving water, fuel, air and steam. For every level of production the engineers introduce different subprocesses to recover the maximum possible energy: steam reheating, fuel preheating, tempering, air heating, etc. All of those processes combine different flows of the fluids available in the plant to prepare them for introduction into the turbines, or to extract the maximum heat available before they are returned to the atmosphere, rivers, reservoirs, etc. The selection of processes is not repetitive as the requirements of, for example, steam for auxiliary processes vary.

Although heat exchangers are optimally designed when they are installed, as time passes the yield of the processes varies even for the same levels of inputs and outputs. This effect is due to ageing of the utility components, manifested as metal creep and fatigue, slag adherence, tube wear, etc. Also, process conditions determine the level of heat exchange, for example temperatures, flows, pressure, speed, air composition, etc. Finally, other factors such as the type of fuel are significant: to be more flexible, many utilities are prepared to use different kinds of fuel (national and imported coal, fuel-oil, natural gas, COG, BFG, and even tyres), and this introduces a new uncertainty factor. The different power capabilities of each combustible produce differences in the behaviour of the plant, and consequently in their efficiency.

Some of those problems are corrected yearly during the annual maintenance, others require specific actions, but this schema is not optimal from the economic viewpoint. The best procedure would be to detect the real state of each component in every case in order to act specifically on it. However, the changing and complex environment makes it very

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difficult to accurately predict the behaviour of the installation for each charge and process condition.

The existence of a high number of heat exchanges makes possible the construction of several partial models, each with its own characteristics and conditions of ageing, heat transmission, etc. So, a quasi-optimal design is possible for each kind of heat exchanger [1–3]. On the other hand, subsystem modelling is still required for process control [4–6].

In the same way, some researchers use intelligent modelling (neural networks, fuzzy logic, artificial intelligence, etc.) to simulate processes [7–9] or heat exchangers [10–12]. Following this, we apply neural network modelling in the thermal power plant of *Aboño*, owned by *Hidroeléctrica del Cantábrico*, a medium-sized Spanish electricity producer. In particular, our research is focused on its first group, with 500 MW. A functional decomposition has been done as a first step to determine the different elements of the process individually based on data. A first model was analysed and designed for the water preheating circuit showing the validity of the technique [8]. Here, a more complex element, the air preheating in a rotating exchanger, is used determine in any case the transmission coefficient instantaneously, i.e. the status of the exchanger and the efficiency of the process.

Intelligent forecasting is going to be very useful for the global study of utilities, either for monitoring [13,14], or control [15–17]. However, it can also help in the decision and diagnosis of partial elements [18,19]. One important choice is the substitution or cleaning of a pipe, exchanger, etc., because power generation is stopped at a huge cost. Our work, like that of Isasi-Viñuela [20], is focused on knowing the time at which to do that, saving an important part of the cost in plant maintenance.

2. Air Preheating and Rotative Exchanger

Air heating is not essential for small boilers, but it is required in big units such as that selected in this case, which uses pulverised coal, for coal drying. For similar working conditions, the efficiency of the steam generation unit was increased globally by around 2.5% per 100F of fume temperature decreasing [21] (see Fig. 1). The use of hot air improves the burning conditions at any load, and reduces the size of the boiler necessary.

The rotating exchanger is used to extract the maximum energy from the fumes to preheat the air. Regenerative rotating heaters are composed of accumulation units heated progressively by the fume

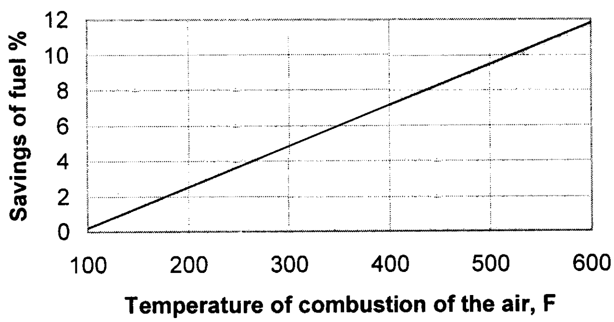

Fig. 1. Improvement of cycle performance with pre-heated air.

flow. Rothemuhle type exchangers use a stationary set of units between two symmetric air inputs and the fumes input in the middle (Fig. 2). The flows are rotated, so the storing units can be kept static and built with materials more resistant to acid corrosion. The rotating mass is only 20% of the global weight of the heater, and the rotating speed is very low (less than one round per minute).

Generally, the reliability of this step is calculated by means of tabulated values and charts. That is a

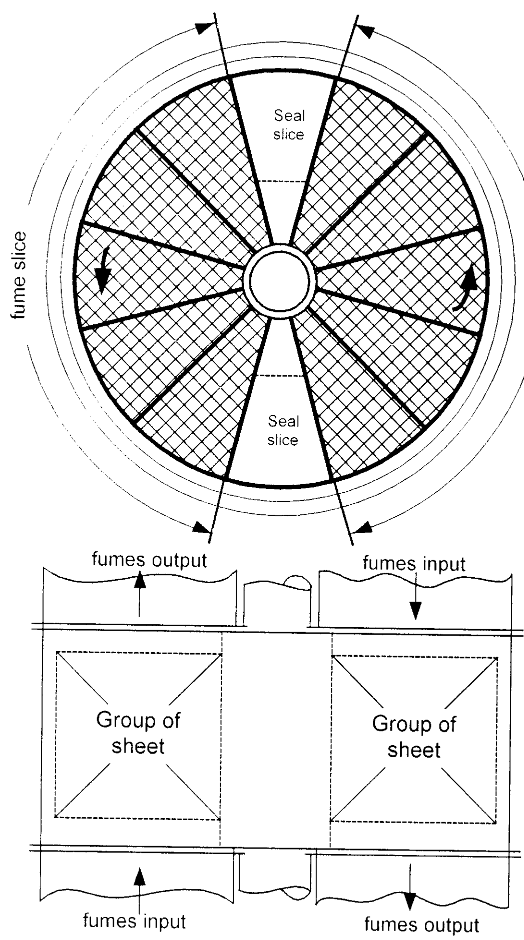

Fig. 2. Exchanger schema.

good approximation, but even in a brand new installation, conditions of the heat transference could be unknown if tests are not done directly on it. The roughness of the surface, real dimensions, porosity, and other variables difficult to measure, may introduce errors in the predictions. Anyway, tests are not efficient enough as the behaviour changes in time, and they should be repeated frequently.

The smoke is largely the cause of the problems, as it can react with the wall covers, and it also transports slag and other solid particles with high adherence. Oxidation attacks and material deposition produce changes in the conductivity, and consequently, exchanger yields vary. The problem could be solved by cleaning the equipment (residuals of the fuel burning are cleaned with special blowers of steam or air), but this requires a programmed stop or implies a consumption of pumped air or steam.

The temperature of the cold side must be controlled to avoid corrosion and obstruction, but also because slag could catch fire. Experience shows that corrosion appears when the metal temperature is lower than a given value. That value must be established empirically, and it depends upon the ratio of the minimum metal temperature, the air and fume temperatures, the type of fuel and the design. When the load is low, the metal temperature is smaller and the deposition of slag is greater. Slag has a tendency to separate off cold metallic surfaces, especially when its temperature is down enough under the softening point. Slag also produces erosion, and this is the cause of further damage and hot points with changes in transference behaviour. The limitation of speed is not protection enough, as slow main flows do not warrant high local speeds. The control of the metal temperature is generally done with a bypass of the input air, recycling a part of the hot air or using steam from the turbine. All those solutions produce losses in the cycle, and in consequence, a decrease of the global efficiency.

As the slag and wear begins to act, the process deviates from expected values. Operators can detect problems as they observe changes in the efficiency of the process, but there are so many subprocesses in the global utility, the quantity of information is so huge and the relation between variables is so complex, that it is not possible for them to detect the source of problems with classical techniques.

The exactness of the transmission calculus would provide a basis upon which to fix exactly the flows of every fluid, saving pumping costs, optimising efficiency and decreasing the maintenance.

There are two main physical effects in the regenerative exchanger: pressure losses and temperature transmission.

The heat transference in the Rothemuhle chamber can be considered as a combination of conduction, convection and radiation. Some gases, mainly CO_2 and H_2O, have important radiation properties, so this type of heat transference cannot be discarded in the fumes flow. Gas emissivity changes with temperature and with the existence of other mixed gases, and total flows are a function of the radiating surface. The capacity of transference is related to the storing properties of material, and it obviously depends upon its own conductivity. However, conductivity is not uniform, as there is a surface film with poor characteristics. The thickness of that film and its degree of coherence will have great importance in the global performance. Unfortunately, it is not possible to know exactly those characteristics without empirical testing, and it is still more difficult to monitor it frequently to consider ageing. Conductivity in gases is dependent on temperature, so the type of gas and its temperature must be introduced for modelling. Traditional equations for heat transference introduce those film coefficients to consider the difference.

The resistance to heat transfer is composed of several factors:

$$R = \frac{1}{\left(\dfrac{1}{R_{rg}} + \dfrac{1}{R_{cg}}\right)} + R_{tw} + R_{cs}$$

where R_{rg} = radiation film resistance of the hot fluid; R_{tw} = conduction resistance of storing material; R_{cg} = convection film resistance of the hot fluid; and R_{cs} = convection resistance of the cold fluid.

Those values could be found by laboratory tests under ideal conditions, but ordinary values are applicable to utilities using coal and fuel with completely clean surfaces with perfect flows. Experience shows that the conductance of fumes is greater when gas is used due to better cleaning of the heating surfaces. Experimentally, values of the so-called cleaning factor vary from 1.2 for natural gas to 0.8 for coal. Anyway, this is just a general approximation, and it cannot be considered as an accurate estimation at all. The value of the coefficient changes in time, and it is especially difficult to calculate when several different fuels are used in varying proportions, as in this case. Then, total transmission will be unknown in most of the cases.

The pressure descent is a main effect in the exchanger. A part of the decrease is due to the changes in temperature, but it also includes problems in the sealing, and it is a reference of inner cleanness.

Simplifying the model in a tubular exchanger, it is possible to approximate the pressure losses by the following equation:

$$\Delta pf = f(L/d_i)|460 + (t_1 + 2t_2)/3|(G_g/10^3)^2/14.400$$

where

Δp_f = difference of pressure	G_g = fume mass velocity
L = length	d_e = equivalent diameter
d_i = diameter	u = absolute viscosity
t_1 = fume input temperature, F	ϵ/d_e = relative roughness
t_2 = fume output temperature, F	f = friction factor related to values of Re and ϵ/d_e
Re = $Gd_e/12\mu$ = Reynolds number	

It must be increased, with input and outputs losses given by

$$\Delta p_e = 1.5|460 + (t_1 + 2t_2)/3|(G_g/10^3)^2/173.000$$

For the air, losses are similar:

$$\Delta P'_f = (fL/d_i)v|G/10^5|^2$$

Unfortunately, the values of the coefficients, as in the case of temperatures, are unknown, and mathematical modelling is not possible without error.

3. Problem Approach and Data Analysis

Any study on the industrial problem begins with the determination of relevant data. Experience dictates some relevant variables that are well known by the technicians. The initial 1800 variable set was reduced to 150 directly involved data, including pressures, material characteristics, working models and several flags. As the process presents a very slow response to changes, data were collected every five minutes, so that every value is a mean of the values during that period. The maximum and minimum of every period were also stored to detect possible problems.

The objectives were to:

- determine the current situation of the exchanger in order to recommend cleaning actions, with the objective to inform the operator of possible process deviation; and
- predict numerically the behaviour of the chamber, in order to integrate the system into the control of the input flows.

For that objective, different techniques were used: clustering, statistical and projection techniques to process the data, and supervised neural networks to build the model.

In any case, both approaches require a detailed pre-processing of data. From past experience of the same research group, it has been proved that pre-processing requires more effort than any other task, around 80% of global effort in the neural modelling of a problem [22]. Also, results are directly related to how good is the pre-processing step: The insertion of incorrect data could destroy any modelling capability.

Incomplete patterns, incorrect values, uncertainty, etc. limit data from sensors. The possibility to introduce only those samples with all the data was discarded, as in this case it is necessary to introduce the temporal effect in the training, and data must be ordered consecutively. The approach to modelling is based upon avoiding the introduction of errors [23], following the next steps:

- Incorrect variables are discarded in any case. They were often found in temperature measurements.
- Data is filled if it is strictly necessary, for example to follow a sequential order. After discarding more complex methods due to the noise generated in trials (EM algorithm, autoassociative networks), data was filled with:
  1. Mean between the previous and next values if variables are considered time-dependent, mainly used in temperatures.
  2. The value of the variable found in the closest representative pre-existing pattern found as the centroid of the hyperspheres clustering algorithm. This case was applied, for example, to the percentage of fuels used.

All those transformations were done in parallel easily with a tool we developed called *XDPM* (implemented in Spanish to be used for technicians), comparing the results and selecting the most adequate technique in every case.

The study of the significance of a variable and its introduction in the neural network is difficult by the special formats they have (such as date types, ordinal variables and alphanumerical values). Dates were transformed into relative values and ordinal numbers codified in binary form when the significance of the order was unknown. The same decision was applied to the alphabetic variables. The preferred binary codification was ‘semaphore’ due to the optimal combination of the number of inputs and resolution. One input for each class was used when the number of classes was less than three.

Other processing tasks were:

- Univariate statistical processing, including mean, variance, maximum, minimum, kurtosis and skewness, and tests on fitness to normal distribution. This process detects problems as values out of range, poor representativity of the variables, etc. that will not be discovered after normalisation.

- Frequential domain transformation. There is a temporal component in some of the variables that could be analysed in the frequency domain. A simple look at the data shows the inherent noise present in the industrial data (Fig. 3). The representation of the data discovers the existence of a high frequency component. The study showed that the component was undesirable and due to sensor limitations and the condensing effect of sampling. A Fourier transform and a frequential filter was applied to remove that component in the variables where it was detected.

Reduction in the number of variables (inputs). The search space must be limited for a correct performance of the techniques for prediction. The Space Emptiness lemma shows that a bigger dimension of the space seems to be emptier. This principle can be obtained studying the volume of the space. If the space is considered hyperspherical, the volume of that space is done by:

$$V_{n(r)} = \frac{\pi^{\frac{n}{2}} r^n}{\Gamma\left(1 + \frac{n}{2}\right)}$$

where n = dimension of the space, and r = radius.

So, if we pretend to have at least one sample (point) for every volume unit, for example for $R = 10$, it is necessary to have 20 samples for dimension 1, but more than 5.10^6 for dimension 6 and the number grows exponentially (Fig. 4). In general, it is not possible to acquire so many samples in industrial data without using artificially generated data, with bootstrapping or other techniques. On the other hand, even with enough data, the number of possible local minima grows, and it will be very difficult to find the global optimum. Fortunately, the input space in industrial cases is not complete as relations between variables introduce restrictions in their ranges of variability, and the number of samples necessary can be reduced.

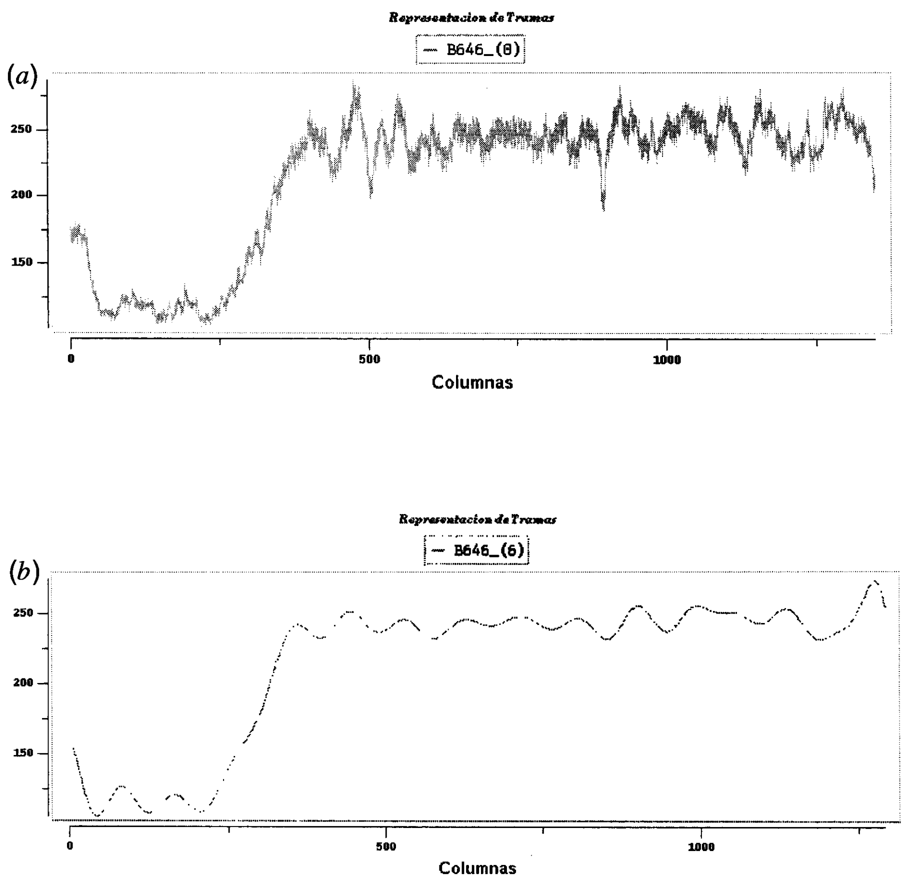

Fig. 3. Frequential filtering of data done with XDPM. (a) Values of an input variable (differential fumes pressure) as sampled. After applying the frequential filtering, the new data is shown in (b).

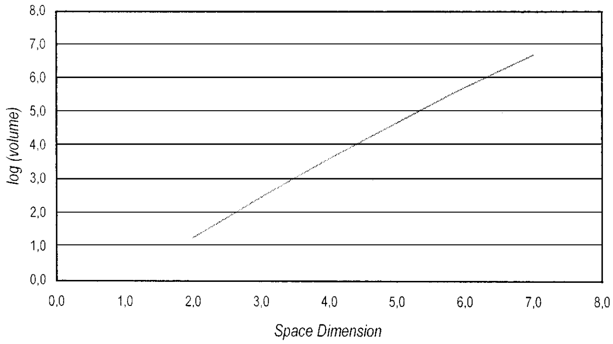

Fig. 4. Logarithmic representation of the number of volume units against input space dimension.

The reduction is done with two different groups of techniques:

- Statistical processing, including correlation, univariate distributions, matrix covariance analysis and non-linear multiadaptive regression splines.
- Projections of the multidimensional space on a bidimensional map of the samples are a very intuitive way to detect influences or relations between variables. Anyway, variables are analysed individually before discarding, because the reduction, except in the rare case of manifold, always produces information losses.

A total of 10,800 data corresponding to 35 days in two groups was collected. After pre-processing, the number of variables involved in the process was 23. Some of them as input and output temperatures were strongly correlated, but obviously they could not be eliminated. With such data, and according to the Empty-Space lemma, we should not include more than seven or eight inputs to have a good representation of the space. The importance of the 23 variables were evaluated with the pre-processing techniques and the most relevant eight variables were selected for training.

4. Neural Modelling

The model to be developed must determine the behaviour of the exchanger, producing the right value of the air and fume temperatures after it. There is an obvious relation between the output temperatures of fumes and air, as the heat is transferred from one to the other. It is necessary to determine the inputs for the model, the outputs and the algorithms and the topology of the network.

The process is very static, and there is a clear time-dependent effect, so it is necessary to introduce not only current values, but also some information about previous steps. The introduction of that information is possible in two ways:

- Using time delay networks. This type of network directly inserts a window of past data in a so-called memory field. The algorithm is then quite different to traditional MLP.
- Introducing the data directly as normal inputs in the structure of a classical steady-state network as a backpropagation based MLP or semi-recurrent networks such as the Elman type.

Results with time delay networks showed instability and deficient accuracy, so the technique was abandoned.

In the case of MLP, the time dependency was accumulated in a new variable. Projections and statistical processing show the influence of pressures, input temperatures and flows as presumed, but also the contribution of other variables such as fumes composition. There is no online measure of fume composition, but this is especially interesting information. A new variable was created representing the degree of slag in the fume. A relative number named ‘cleanness’ was assigned to each fuel (coal, COG, natural gas, BFG and fuel) and multiplied by its accumulated flow. That variable represents in some way the quantity of slag produced during the lifecycle. That variable is reset when maintenance tasks are done. Another variable is generated with the percentage of fuels being used some minutes before. Its value is not accumulated, and represents the composition of the gas in that moment. Those two variables were added to the process data and introduced in the model.

For any kind of simulation, data was divided in the 75%(10%) – 25% structure for training – cross-validating – testing and normalised between 0.1 and 0.9. Cross-validation fixed the number of training cycles in order to achieve the best performance without risk of overtraining: three consecutive worse results in the validation data provoke the training to stop. Data was introduced ordered by date in the network (without being shuffled). This kind of train-

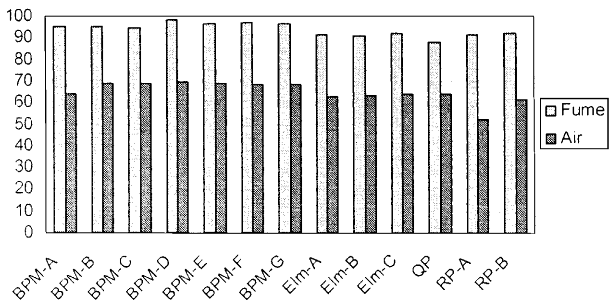

Fig. 5. Forecast temperature success ratio.

ing allows the network to remember the inherent sequence of data in time.

As temperatures are related between them and their combination is limited by the total energy, the first approach was the creation of a unique model for both outputs: air and fume temperatures. This model should produce values in the valid region of the outputs. A summary of the different results is shown in Table 1, and overtraining in the temperature of the fumes makes it impossible to fix adequately the temperature of the air. Best average results were 95% and 69%, respectively, for a 5% tolerance. Unfortunately, as the number of inputs grows, the neural network provides a worse performance. If we pretend to forecast both temperatures, the connections between the first and second layers must be used for the prediction of both variables. Only the second to third layer weights strictly represent the difference between both temperatures. The results show poor performance of the global model due to this fact.

A second approach was the use of two independent models with a network for every output. A summary of various results is shown in Table 2 and Fig. 6.

Results improve the first case, especially in the worst output (air temperature). This method could be problematic as both results are not related in the model, but they are in the real case. Anyway, there are no restrictions by the number of patterns, the number of parameters is now double, avoid partial overtraining, and allows the configuration of networks with different topologies for every case. The success of the model can be also appreciated in the distribution of outputs. Industrial models must be conservative, preferring results that are not so accurate but limiting errors to a very narrow range. In the other case, severe problems could occur with the equipment. Those models produce restricted values, centred on zero error, as seen in Fig. 7.

Table 1. Summary of results for the model with two outputs and different neural network topologies. Backpropagation with momentum (BPM), Elman (Elm), Quick propagation (QP) and Resilient propagation (RP).

Hid.	α	Algorithm	% Success	
			T_{fume}	T_{air}
9	0.2	BPM-A	94.9	63.5
12	0.2	BPM-B	95.2	68.7
12	0.8	BPM-C	94.3	68.5
14	0.2	BPM-D	97.9	69.4
14	0.8	BPM-E	96.6	68.9
15	0.2	BPM-F	96.7	67.8
15	0.8	BPM-G	96.5	68
9	0.3	Elm-A	91.4	62.8
12	0.3	Elm-B	90.9	62.9
14	0.3	Elm-C	91.8	63.6
9	0.8	QP	87.7	64
9	0.2	RP-A	91.2	52.3
14	0.9	RP-B	92.1	61.2

Table 2. Summary of results for two different models of one output each.

Hid.	Algorithm	% Success	
		T_{fume}	T_{air}
10	BPM-A	98.2	89.2
14	BPM-B	97.9	92.9
10	Elm-A	95.6	86.6
14	Elm-B	96.7	87
10	QP-A	96.5	85.4
14	QP-B	96.1	86.9

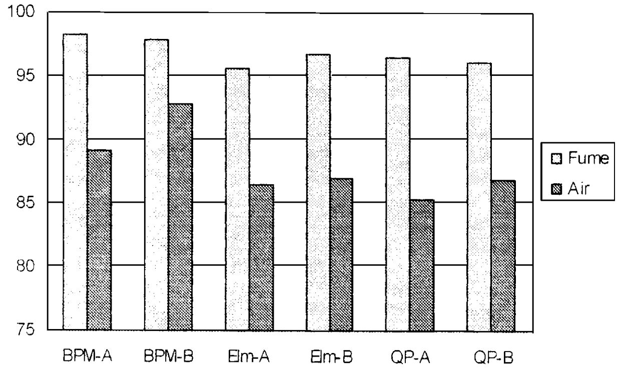

Fig. 6. Forecast temperature succes ratio.

In both cases, Elman networks are more stable, with uniform results but worse performance. Backpropagation algorithms with momentum and weight decay are always the winners, although the training time is usually higher.

The results show a different behaviour between both outputs. It seems that the temperature descent of the fume is easier to predict than the increment of the air temperature. This fact is assigned to the dissipation effect of the materials in contact with the exchanger, producing losses of energy, mainly by conduction.

A new approach that is currently under development is the prediction of the transmission coefficient, in order to study their variability directly.

5. Conclusion

Complete modelling of the heat transference in a power utility is not affordable as the number of

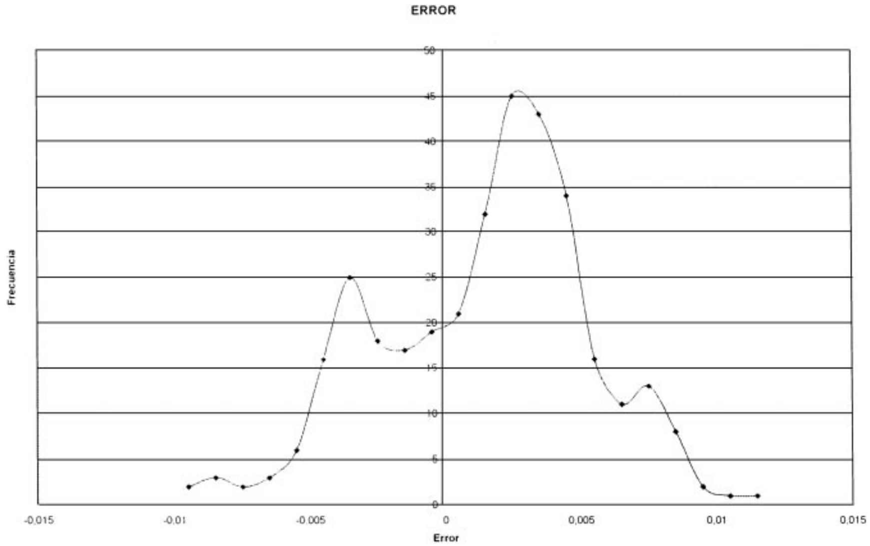

Fig. 7. Distribution of errors of model output.

variables is too great and problems arise with the representativeness of the data and the so-called 'empty space'. A more accurate modelling of a regenerative exchanger has been provided, introducing variables other than input and output flow, input temperatures and changes in pressures. Those new values mainly represent the effect of slag on the heat transmission.

Generation load and speeds are other variables introduced to complete the input set, rejecting the possibility of introducing several values of the same variables in past times to consider thermal inertia, wear and ageing.

Data provided by sensors is poor and full of errors, so a previous filter was done in the frequency domain to extract model inputs. With those values a double approach was used: modelling with neural networks and preconditioning with projection techniques. The neural model outperforms the current modelling, so it can be affirmed that they imitate the process better than traditional techniques.

The results open a new path for complete process modelling and optimisation. The advantages of this approach are obvious, as currently there are no other tools to predict this problem, and maintenance and process control will be improved and facilitated with the diagnose. Currently, further work is being done to export the results to other heat exchangers in the utility, and to detail levels of corrosion, wear and dirtiness. Also, a condition monitoring tool based on non-linear analytic projections has been created in order to provide the technicians with a powerful tool for process supervision.

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