ECI Symposium Series, Volume RP5: Proceedings of 7th International Conference on Heat Exchanger Fouling and Cleaning - Challenges and Opportunities, Editors Hans Müller-Steinhagen, M. Reza Malayeri, and A. Paul Watkinson, Engineering Conferences International, Tomar, Portugal, July 1 - 6, 2007

CFD AND NEURAL NETWORK-BASED EXPERT SYSTEM FOR THE SUPERVISION OF BOILERS AND FURNACES

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ABSTRACT

CFD (Computational Fluid Dynamics) tools were used to build a "virtual" furnace, validated with experimental data. This model was used to simulate both normal and “faulty” behaviours, regarding parameters such as energy conversion efficiency, steam leakage and fouling. A database was developed comprising normal situations and simulated fault sets, characterized by virtual sensor outputs used in the evaluation of diagnostic parameters patterns to be processed and recognized by the diagnostic system. The database was processed using Neural Networks, with satisfactory results even in their most simple form (backpropagation networks) trained using standard algorithms. Pattern recognition was thus performed, identifying root causes of simulated anomalies. Interactions with related research areas and future proposed developments are also discussed.

Keywords
Diagnostic Systems, Computational Fluid Dynamics, Fault Diagnosis, Pattern Recognition, Neural Networks, Sootblowing Optimization.

INTRODUCTION

The importance of a diagnostic system in any industrial hardware cannot be overstated, considering their mounting purchase and operation costs, an increase in their availability and reliability being thus desirable, though not only for economical reasons, considering the human consequences any major industrial accident can have. Past decades have also witnessed growing concerns over environmental issues, made evident by stringent legislation on pollutant emissions. Aside from economic implications in terms of fuel consumption and cost, the efficiency of the combustion process impacts on the formation of pollutants such as NO_x, SO_2, CO, unburnt hydrocarbons and solid particles. In particular for boiler applications, a diagnostic system should assess at least three main parameters: combustion efficiency, fouling and the occurrence of steam leaks.

Fouling occurs as a deposition of solid particles on boiler surfaces, decreasing heat transfer to the working fluid and strongly impacting performance. A correct assessment of fouling is invaluable in establishing effective sootblowing strategies, with obvious energy cost benefits (Afgan *et al.*, 1996).

Steam leaks are evidence of hardware degradation that could have been prevented if adequate measures had been taken, albeit being very difficult and expensive to forecast in most cases, namely for medium to small boilers. The assessment of their severity and their location is essential in deciding whether or not to stop the operation or repair damages on-line, rather than letting incipient leaks develop if they're unlikely to worsen and if their effect is negligible (Afgan *et al.*, 1998).

Pollutant formation is a consequence of the properties of the fuel being burned and of furnace conditions in terms of fuel-to-air ratios or temperature and flow fields. A judicious adjustment of these conditions, using information provided by a diagnostic system, may enable adequate control and minimization of pollutant formation and efficiency increases.

Burning fuel in a furnace is a process in which complex phenomena such as combustion, turbulence, different heat transfer modes (radiation being dominant given the high temperatures) and fouling take place simultaneously, thereby affecting the temperature, flow and radiation fields.

Standard analytical models have been used in more or less simple instances, but their applicability diminishes as the complexity of the system and the occurring phenomena increase. Industrial processes are usually characterized by nonlinear, time-varying behaviour, and multiple-input/multiple-output situations, rendering the attractiveness of alternative modelling techniques obvious. A comprehensive overview of fault detection and diagnosis methods can be found in various references (Venkatasubramanian *et al.*, 2003).

The proposed framework relies on using CFD and ANN in an integrated way. Diagnostic systems are usually developed *a posteriori*, i.e. after the hardware they are meant to support is fully developed, the knowledge acquired during the operation of the equipment being the foremost tool on which the system is based. Adequate CFD simulations of faults should anticipate most of the operational situations to be recognized by the diagnostic software. The simultaneous rather than sequential use of these techniques should produce synergies that will benefit the processes of designing and developing the hardware itself, as well as its diagnostic systems. Given this simultaneous approach, the results of applying each technique can be used by the others, enhancing their usefulness and fine-tuning the solutions they provide.

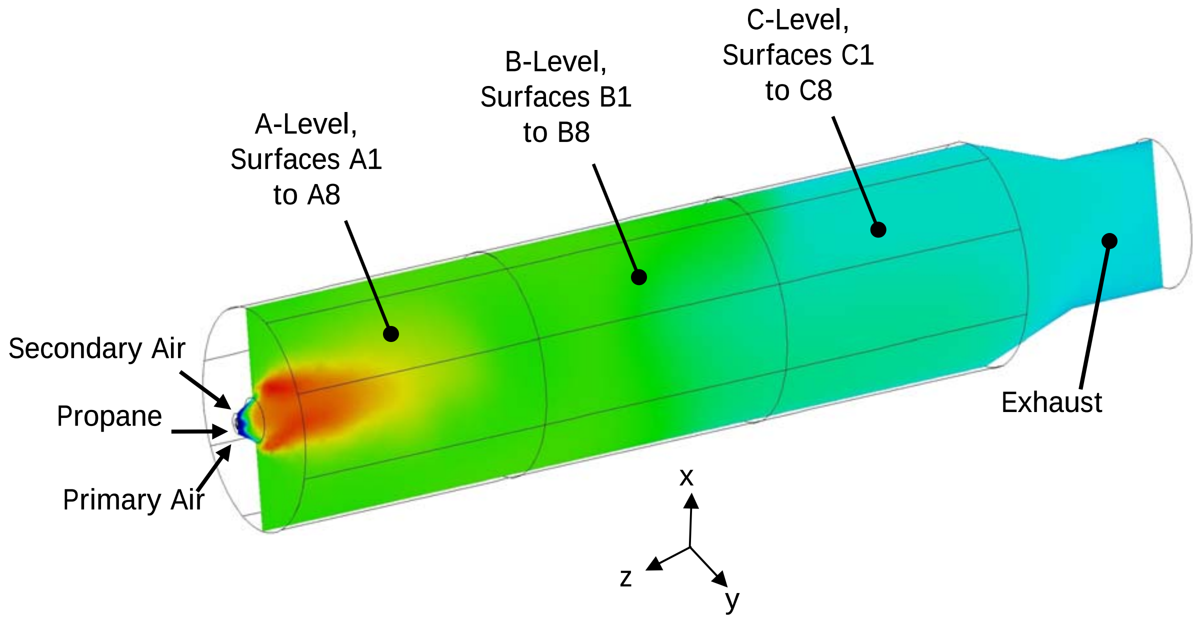


Fig. 1 – General furnace arrangement and diagnostic surfaces.

CFD software was used to model a "virtual" furnace. The potential this tool demonstrated in the simulation of existing equipment and in assisting the design of new hardware became readily apparent, together with its extreme usefulness both in the simulation of abnormal situations and in the generation of "pseudo-historic" operative values to be used in monitoring and diagnostic systems based on historical data. These consist of both normal behaviour and faulty sets intended to be representative of the occurrence of abnormal situations, comprising a number of diagnostic system inputs representing the virtual sensor readings, which in turn characterize various fault patterns.

The use of ANN reduces the need for the complex modelization associated with quantitative model-based approaches, since they are inherently immune to noise, although incapable of extrapolating beyond their training scope with any reliability. ANN can be used to process the database with satisfactory results even in their most simple forms, i.e. feedforward backpropagation networks using standard training algorithms, in order to perform a pattern recognition which allows the identification of the root causes of simulated anomalies. This use of ANN for diagnostic purposes in thermal applications, namely regarding the evaluation of fouling, is becoming fairly commonplace in recent years (Romeo and Garreta, 2006).

Assuming its results can be regarded with a fair degree of confidence, based on experience and validation, the CFD model is invaluable in the process of testing various design options before physically implementing them, even if at a prototype stage, thereby minimizing development time and cost. Throughout this process, CFD results can be used in designing a proper diagnostic system, based on the simulation of both normal and abnormal situations liable to be encountered by the hardware. Further refinements made during the actual use of the hardware are inevitable, but the diagnostic system can be tailored to specifications and needs identified in the simulations, reducing setup and fine-tuning times.

NUMERICAL MODEL VALIDATION AND DATA PATTERN GENERATION

CFD software was used to model a "virtual" furnace, using boundary conditions which characterize operational parameters, along with other system characteristics. Suitable experimental data about propane combustion in a 500 kW furnace were available, justifying the use of this system as a reference and as a means of testing and validating the CFD methodologies and the development of the diagnostic system.

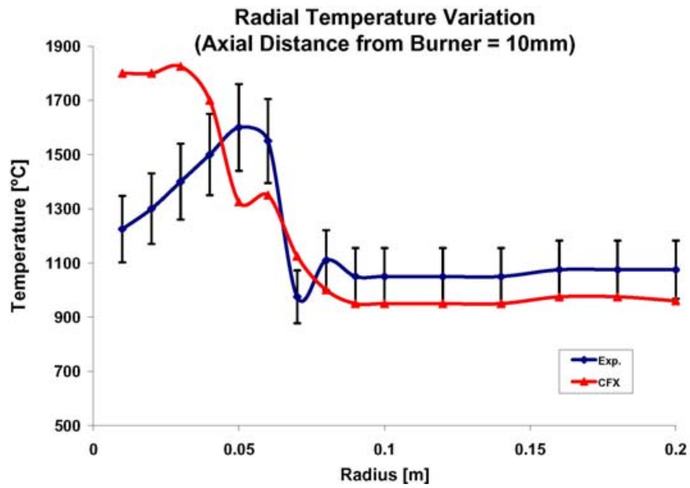
The CAD definition of the geometry and its importation to the CFD package were straightforward. Mesh dependence and processing time studies were then conducted, while testing and comparing options regarding reaction, turbulence and radiation models. Qualitative temperature, flow and radiation fields obtained show a good adjustment with expected patterns, confirmed quantitatively with available experimental data about temperature and reactant concentration profiles, validating a baseline "normal" pattern.

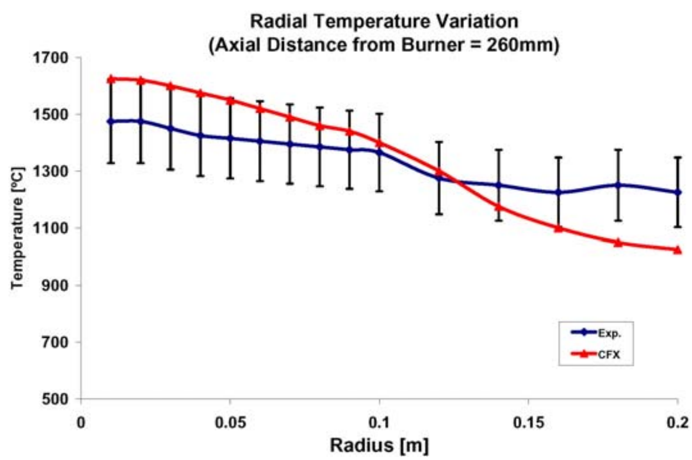
Illustrated in Fig.1 is the general furnace arrangement, showing namely the fuel and air inlets, the exhaust and the surfaces considered for diagnostic purposes.

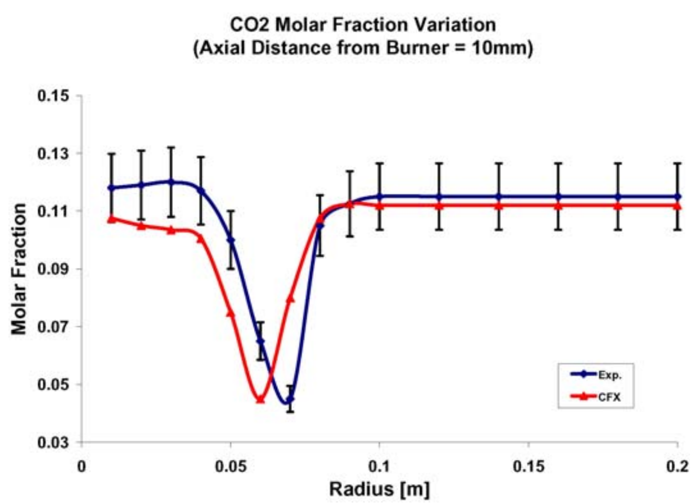
The experimental furnace is used for various combustion experiments, being fully equipped for data collection purposes. The vertical furnace consists mainly of eight cylindrical segments, each measuring 0.3m in height. This combined height of 2.4m is augmented by an exhaust section at the bottom and by the burner arrangement at the top. The experimental values and a detailed description of the furnace can be found in (Azevedo, 1998), resulting from propane combustion studies under various swirling flow conditions. Also found in this reference is a complete list of the boundary conditions used in the simulations, namely primary air, secondary air and propane inlet velocity profiles (including swirling components), as well as exhaust conditions. A purposely measured wall temperature profile was also used in the model.

Fig. 2 illustrates a comparison of experimental temperature and reactant molar fraction profiles (with 10% error bars) with simulated values. The adjustment between experimental and numerical curves improves as the vertical and radial distances to the NBR (Near Burner Region) increases, due to the notorious difficulty in simulating the phenomena occurring in its vicinity. This is repeatedly mentioned in literature, being due to the simultaneous occurrence of various phenomena, i.e. highly swirling flow (Ss = 1.0), combustion (modelled using the Eddy Dissipation Model), turbulence (modelled using various models but with k-ε giving satisfactory results and RSM being slightly more accurate but somewhat heavier in terms of computational effort), radiation (simulated using various models, with Discrete Transfer with 8 rays giving the best results), etc. The expected occurrence (given the swirling flow) of the thermoacoustic phenomenon known as PVC (Precessing Vortex Core) was also verified and accurately simulated (in terms of angular frequency) according to the available literature. All profiles were measured in the topmost (and closest to the burner) furnace cylindrical segment. The simulated chemical species concentration profiles also displayed a generally good adjustment with the experimental values.

Once a baseline "normal" pattern is generated, taking into account non-abnormal variations not associated with faults and induced by factors such as turbulence, CFD is used to simulate fault situations which will be used to develop the diagnostic system. Within the present context steam leaks, surface fouling and various combustion efficiency situations can be considered, the obvious *caveat* being the unavailability of experimental data, emphasizing the importance of previous validation work in building- up confidence in the CFD tools.







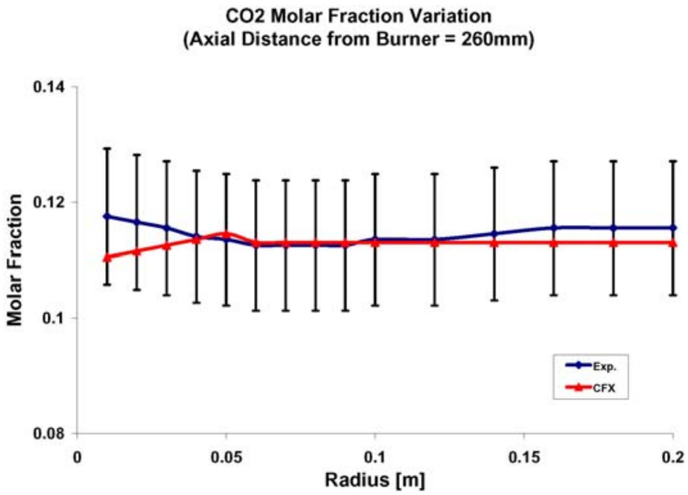


Fig. 2 - Comparison of experimental temperature and CO2 concentration profiles with simulated values.

In order to analyze the aforementioned phenomena, a study of underlying physical-chemical processes is necessary in order to identify the relevant variables that enable their characterization and diagnosis. Concerning fouling, the formation of low-conductivity deposits in heat transfer zones is undesirable because of the performance degradation entailed. Fouling study has dealt mainly with its mechanisms, structure of deposit, relationship with other parameters, as well as origin and composition of the fuel itself, concluding that it affects efficiency mainly through the emissivity, thickness and structure of the deposit, and emphasizing the difficulty of its study due to the complexity and interrelationships of the parameters involved. Most of the heat generated within the furnace is transferred to the working fluid trough radiation, with a smaller contribution through convection. The thermal efficiency of the furnace surface can be used as a fouling evaluation criterion, being defined as (Afgan *et al*., 1996):

$$R = \frac{q_{net}}{q_{inc}} = \frac{q_{not\_clean}}{q_{av}} \quad (1)$$

where q_{net} is the heat flux on the boiler surface, q_{inc} is the incident radiation on the surface and q_{av} is the average surface heat flux for the total heat generated in the furnace. Radiation heat flux on the fouled surface is identical to the net heat flux at the same surface. Assuming the surface temperature of the clean surface is sufficiently low, the clean heat flux will be identical to the incident radiation heat flux. This criterion has been used in the present work.

Regarding steam leaks, their diagnosis can be approached in a similar fashion as fouling, but in this instance the ratio selected is between incident radiations for cases with and without steam leaks being present, so that the leakage assessment criterion is (Afgan *et al*., 1998):

$$r = \frac{q_{leak}}{q_{normal}} \quad (9)$$

The diagnostic of both fouling and leakage situations can thus rely on the measurement of heat fluxes, namely using radiometers developed earlier for this purpose (Martins, 1998; Martins *et al*., 1998).

The monitorization of simulated efficiency conditions and pollutant formation can be achieved through the analysis of variables such as reactant mass flows and concentrations, temperature and reaction rate fields or outlet chemical species concentrations.

The simulation setup used in establishing the “normal” situations must be modified in order to account for desired process disturbances. The occurrence of steam leaks can be simulated either by specifying additional inlet boundary conditions or punctual mass and momentum sources,

Steam leakage was simulated by specifying mass and momentum sources at the centre of each diagnostic surface, representing leaks with equivalent diameters of 5, 10 and 20mm. Boundary conditions for these ‘inlets’ were calculated assuming that the pressure difference between the interior of the furnace and a pressurized water circuit would ensure the occurrence of choked flow. The critical velocity for this choked flow was then computed and used to calculate mass flows, turbulent kinetic energies and turbulence dissipation values for each particular mass source.

Fouling can be reproduced using proper mathematical models to simulate the actual physical process or alternatively by specifying varying surface emissivity and conductivity conditions in order to observe the effect of more or less local fouling phenomena in the global pattern of relevant variables. This simplified approach was selected here in order to speed up implementation.

The monitorization of simulated efficiency conditions and pollutant formation can be achieved by the analysis of its aforementioned process variables.

Illustrated in Fig. 3 are CFD simulations of steam leaks, showing them in terms of steam concentrations. The results of these simulations and those of surface fouling can be plotted in order to show their effect on the distributions of diagnostic parameters R and r, as shown in Fig. 4 for leakage and fouling situations in two distinct furnace locations, with normal results and three severity levels for each occurrence. Letters L and F stand for leakage and fouling respectively, the location being identified by the level letter A, B and C and the surface number 1 to 8 (see Fig.1) and increasing severity levels noted I, II and III.

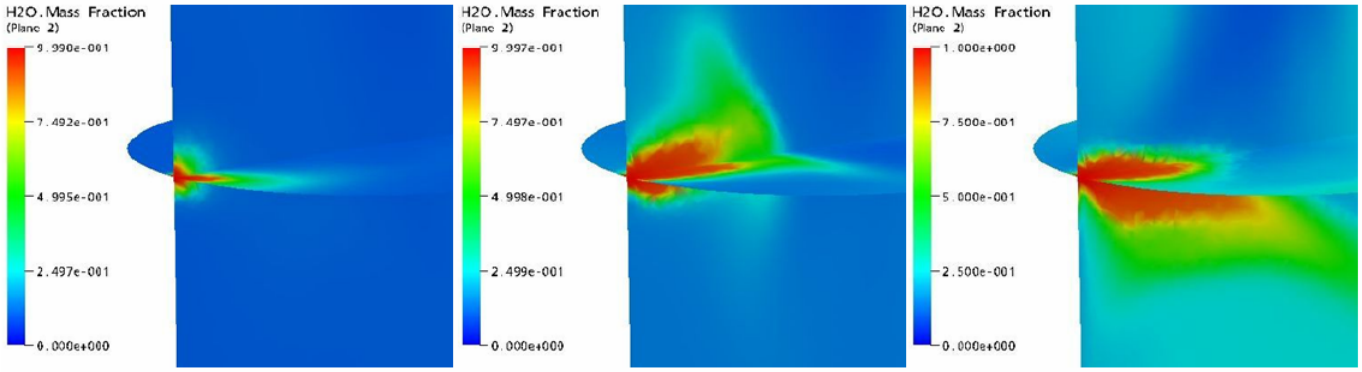
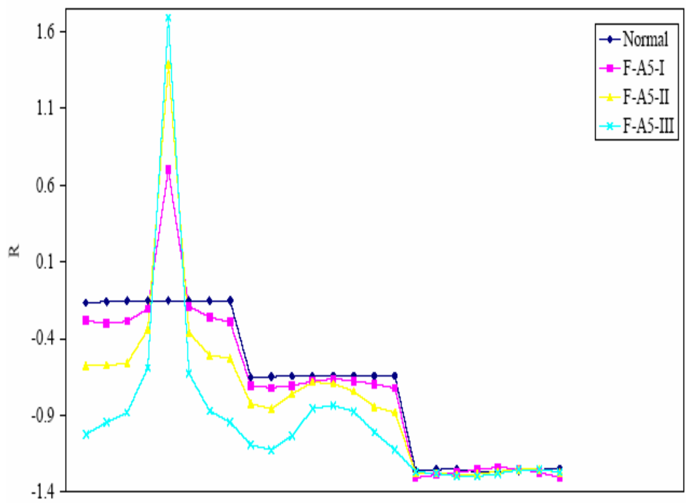
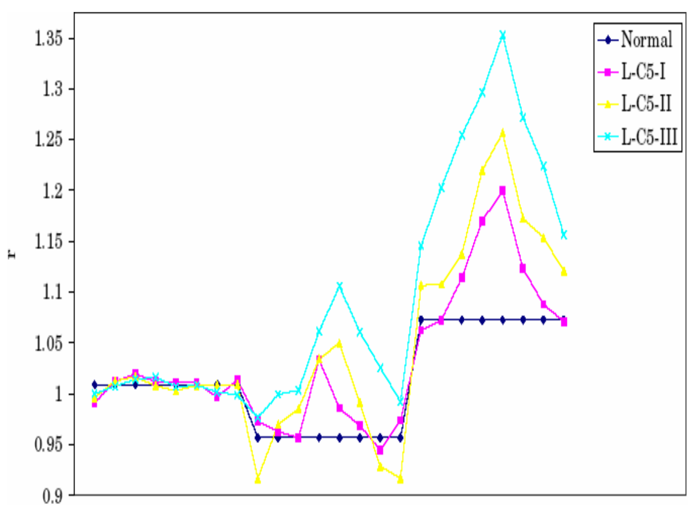


Fig. 3 – CFD simulations of steam leaks.



Variations of parameter *R* – Fouling in A5



Variations of parameter *r* – Leakage in C5

Fig. 4 – Diagnostic parameters distributions for two simulated abnormal situations.

ANN ASSUMPTIONS AND FORMULATION

Once diagnostic variables patterns are obtained via CFD, they can be processed in order to design a diagnostic system using ANN, expected to adequately process the database even in their most simple and widespread form, i.e. using standard multi-layer feedforward architectures trained with the most usual backpropagation algorithms, implemented using the Neural Network Toolbox in MATLAB® (Calisto, 2006; Martins and Calisto, 2006).

ANN (Artificial Neural Networks) reduce modelization requirements compared with quantitative model-based approaches, since they are inherently immune to noise, although incapable of extrapolating beyond their training scope with any reliability. Training adjusts network parameters in order to best represent relationships underlying simulated sensor readings (network inputs) and diagnostic parameters used as outputs.

The CFD-simulated heat fluxes were exported to Excel, where they were processed and associated with the normal or faulty particular scenario they refer to. This process involved data normalization to values in the [-1, 1] interval, their randomization (preventing the occurrence of tendencies associated with the presentation order) and separation into three distinct data sub-sets, usually denominated as training, validation and test sets and typically comprising 60, 30 and 10% of the total number of data sets, respectively (Demuth and Beale, 1996; Looney, 1997).

The reason for this division lies with the very nature of the training process, where the data sets are presented successively to the network, which adjusts its parameters in order to best represent the relationships between the diagnostic parameters used as network inputs and the target pattern identifiers used as outputs. One problem that may occur during training is usually referred to as overfitting. This designations indicates that from a certain number of iterations on, the network becomes overly "specialized" in recognizing the patterns with which it was trained, thereby losing its generalization capability by failing to recognize patterns not used during training.

The problem may be solved by implementing a technique denominated Early Stopping. While the training set is used in the usual way, the algorithm uses the validation set to check the global network error obtained with both the training and validation sets as network inputs, stopping the training when the difference in error between sets reaches an arbitrary value. Training is thus stopped before the onset of overfitting, rather than when reaching either the target error or the maximum number of iterations. After being adequately processed, the data sets can be passed on to MATLAB®, as shown in Fig.5.

The test set can be used to evaluate competing network architectures (essentially in terms of number of layers, activation functions and training algorithms) and the performance of each particular network, namely by computing correlations between trained network outputs and target vectors.

The diagnostic system is supposed to recognize fouling and leakage patterns occurring in a total of 24 control surfaces located on 3 horizontal levels, labelled A, B and C, with 8 radial sectors on each level (as illustrated in Fig. 1). One leakage parameter and one fouling parameter are computed for each surface, in the form of the aforementioned R and r heat flux ratios. Both phenomena were simulated with 3 different intensity levels.

Several options regarding network architecture were considered. In every case, networks using *logsig* output layers (that "squash" the outputs to a [0, 1] range) were used. A modification to the target output normalization was therefore introduced in order to avoid a saturation of the activation function. Since sigmoid functions have low gradients near their asymptotes (i.e. 0 and 1 for *logsig*), maximum and minimum data values of 0.9 and 0.1 were used rather than 1 and 0, reducing risks of convergence paralysis. A variety of training algorithms were tested, namely Batch, Gradient Descent with Momentum, Levenberg-Marquardt, Resilient Backpropagation and Adaptive Learning Rate algorithms (The MathWorks, Inc., 2004).

Given restrictive time and hardware limitations, and rather than attempting to achieve the intended system performance with a single network, a hierarchical approach was used (see (Ogaji and Singh, 2003) for a similar design), in which different tasks were performed in a sequential manner, as illustrated in Fig.6.

This methodology had several advantages, such as smaller input and output vectors, which permit faster and less complex subsequent system "maintenance", thereby enhancing its ease of integration in retrofitting applications. This kind of modular structure has been demonstrated to allow an optimization of each of its components by using different network configurations and parameters, as dictated by requirements (Ogaji and Singh, 2003).

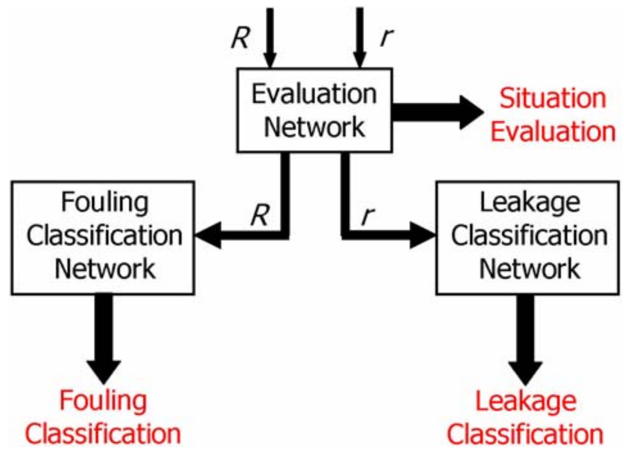


Fig. 5 – Data Flow.

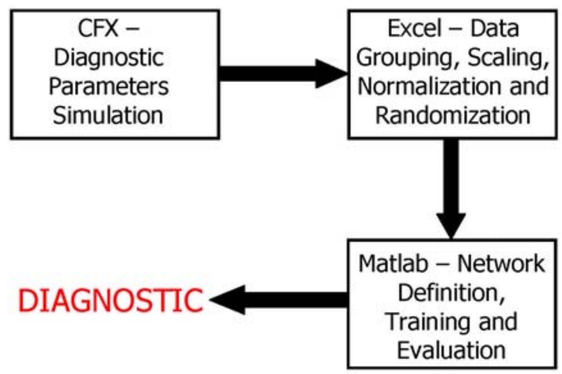


Fig. 6 – Diagnostic System Network Architecture.

In the proposed configuration, a first diagnostic "layer" evaluates the occurrence of abnormal situations, without attempting to classify their severity or location, 48 inputs (24 times R and r parameters) being used. The network's inputs are these simulated R and r values, associated with target values of 0.9 for actual occurrences and 0.1 for non-occurrences, as explained above. The output consists only of two values, the computed occurrence probabilities of fouling and leakage.

Once these probabilities are quantified, the diagnostic system used two "dedicated" networks in order to compute the phenomenon's location and severity. The input of these secondary networks consists of only 24 values of parameters R or r, depending of the phenomenon to be diagnosed. Severity is then evaluated by specifying 72 outputs, corresponding to 24 locations in 3 possible severity levels. This time, these networks' inputs are these simulated R *or* r values, according to the relevant phenomenon. Target values of 0.9 for actual occurrences and 0.1 for non-occurrences are used as explained above.

A limitation of the current approach, to be addressed in future developments, is a lack of multiple fault identification capability. The hierarchical approach allows for a palliative solution, considering that the system's first layer, given its architecture and training process, will not identify a simultaneous occurrence of fouling and leakage, since such a multiple abnormality would necessarily be preceded by the occurrence of one of the phenomena on its own, unless they rather improbably take place at the exact same time.

Once the system architecture is decided upon, particular details of each network must be determined and optimized, based on the performance of various tested options. For this purpose, the correlation coefficient between output and target vector is computed, expressing the adjustment between them. The process is repeated for all vectors in the test set, thus providing an objective comparison parameter between possible network parameters, architectures and training algorithms. Values above 0.8 are usually considered to be satisfactory in this type of application (Sen and Yang, 2000; Kalogirou and Bojic, 2000).

ANN IMPLEMENTATION RESULTS AND DISCUSSION

A total of 73 sets of "normal" values were used, together with 216 sets with simulated fouling and 216 more for leakages. These sets are divided, for each of the 3 networks, along the aforementioned 60-30-10% proportions, yielding for the evaluation network 303, 151 and 51 training, validation and test sets, respectively, while for the classification networks the numbers are 173, 87 and 29 (the evaluation network uses all the CFD data, while the classification networks only use the normal values and those related with each detrimental phenomenon).

The training stoppage criteria used where the maximum iteration number (fixed at 1000), together with an arbitrary global error between iterations (1×10^{-5} in all cases), but it was found that training was always stopped by the Early Stopping routine, due to the onset of overfitting. Table 1 shows the options retained for each particular network, in terms of number of neurons, layers, activation functions and training algorithm, for which the best overall performance was achieved.

Is should be noted that an increase of the number or neurons per layer beyond a certain number, rather than being beneficial, led to earlier onset of overfitting and thereby curtailing proper network training and lessening its generalization capability.

Table 1. Network parameters and training algorithms.

	Neurons per layer	**Activation Functions**	**Training Algorithm**
Evaluation Network	48-200-200-2	tansig-tansig-logsig	Resilient Backpropagation
Fouling Classification Network	24-475-72	tansig-logsig	Resilient Backpropagation
Leakage Classification Network	24-525-72	tansig-logsig	Resilient Backpropagation

No “false” occurrences were detected by the evaluation network, nor were any “real” situations left undiagnosed.

As far as the fouling classification network is concerned, its behavior corroborates some qualitative assumptions. As expected, diagnostic accuracy (measured by computed occurrence probabilities and correspondent correlation coefficients) improved with increasing severities and worsened from A-level (near the burner) to C-level (near the exhaust). The effect of the increased thickness of the low-conductivity layer, for any given surface, is intuitively evident, its local effect being more intense in the near-burner region when compared with the exhaust region due to the temperature gradients present, the increase of surface temperature due to fouling being more evident in high-temperature regions.

Regarding the leakage classification network, on the other hand, performance was worse for less severe leaks located on C-level. A perfectible database, both in terms of case distribution (it was found that the random distribution of simulation results only included one case for C-level in the training set) and of the number of cases itself, may account for this behaviour.

Shown in Table 2 is a summary of the performance of each of the 3 neural networks used for diagnostic purposes, in terms of percentages of test set vectors for which computed probabilities are above 0.9 for actual occurrences, below 0.1 for non-occurrences and the associated correlation coefficients.

The data distribution patterns were adequately recognized despite the relative simplicity of the approach selected, which is undoubtedly somewhat simplified in its reproduction of actual steam leaks and fouling processes. Possible enhancements are discussed below, but the patterns underlying the data were sufficiently well identified in order to clearly illustrate the potential of ANN in fouling and leakage diagnostic applications, even in their most basic and widespread forms and using commercial software.

Table 2 – Network performance summary.

	Evaluation Network	Fouling Classification Network	Leakage Classification Network
Actual Occurrences with P > 0.9	85%	80.1%	83.3%
Non-occurrences with P< 0.1	98%	87.5%	81.8%
Correlation Coefficients above 0.85	Not applicable	83%	72%

CONCLUSIONS

1. The use of CFD tools has shown a good performance in the simulations of the processes that characterize the operation of boilers and furnaces, with very satisfactory validation comparisons with experimental values.

2. ANN have shown excellent potential in circumventing the problems associated with the complex modelization associated with traditional, quantitative model-based approaches, yielding very good results in the pattern recognition used within the present diagnostic paradigm. These results have been achieved even using the most simple and widespread ANN techniques.

3. The continuation of this line of development, including its interaction with enhanced instrumentation being developed, shows good prospects towards increases in performance, ease of integration and more widespread application. The integrated use of CFD and ANN produces synergies that benefit the processes of designing both the thermal equipment itself and its diagnostic and control systems, through the ability to validate and adjust their respective results in iterative steps, reducing development costs.

ONGOING AND FUTURE DEVELOPMENTS

Once training is accomplished the network is ready to be used on-line for diagnostic tasks, with the obvious difference that in its present state readings of actual sensors, rather than simulated values, are used as inputs. Regardless of the selected approach, these must be adequately formatted in order to be read by a Graphical User Interface (GUI). This GUI should provide information about output readings, trend lines and warning/alert levels plots and diagnostic messages regarding fouling, leaks and efficiency.

The status of the various instruments must be monitored in order to identify possible faults, since the validity of the diagnostic is influenced by correct sensor readings. Given the fact that the diagnostic parameters used in this approach rely on the measurement of aforementioned heat fluxes, their evaluation is critical and increases in the performance of the heat flux meters would obviously be beneficial.

The line of development that led to the present work (funded through FCT – Fundação para a Ciência e a Tecnologia, Project POCTI/2001/EME/41349) is being continued, with forthcoming enhancements along two main axes. A fully transient approach to the CFD simulations is desirable. Due mainly to hardware limitations, the present results were obtained mostly through steady-state simulations of each particular situation, rather like still-photography shots that don't necessarily have an explicit time connection between them. A transient approach would give the possibility of making use of time-variant characteristics of measurements, such as the fouling criteria discussed earlier, in order to refine diagnostic processes. On the other hand, a full-scale industrial development and deployment process is being proposed (Project PTDC/ENR/74022/2006), during which the methodologies (other than CFD modeling) will essentially be repeated on a full-scale furnace, both in the acquisition of data for ANN usage and in the validation and demonstration phases.

Concurrently, further development of the heat flux measurement instrumentation is being pursued (Project POCTI/2004/ENR/59662) with encouraging preliminary results (Martins *et al.*, 2006), usage of these enhanced sensors in the full-scale implementation being expected.

REFERENCES

Afgan, N, Carvalho, M. G., Coelho, P. (1996); Concept of expert system for boiler fouling assessment. *Applied Thermal Engineering*, Vol. 16, pp. 835-844.

Afgan, N, Coelho, P., Carvalho, M. G. (1998); Boiler tube leakage detection expert system. *Applied Thermal Engineering*, Vol. 18, pp.317-326.

Azevedo, J.A.T. (1998); Simultaneous Combustion of Industrial Solid Residues with Gas in a Semi-Industrial Furnace. MSc Thesis. IST- Technical University of Lisbon, Lisbon, Portugal.

Calisto, H. (2006); Expert System for the Supervision of Industrial Furnaces. MSc Thesis. Universidade de Aveiro, Portugal.

Demuth, H., Beale, M. (1996); *Neural Network Design*, Brooks/Cole Publishing Company.

Kalogirou, S. A., Bojic, M. (2000); Artificial neural networks for the prediction of energy consumption of a passive solar building. *Energy*, Vol. 25, pp.479-491.

Martins, N. (1998); A New Heat Flux Meter for High Temperature Harsh Environments. PhD Thesis. IST-Technical University of Lisbon, Lisbon, Portugal.

Looney, C. G. (1997); *Pattern Recognition Using Neural Networks*, 1st Edition, Oxford University Press, Oxford.

Martins, N., Carvalho, M. G., Afgan, N., Leontiev, A. I.(1998); Experimental Verification and Calibration of the FLUMET Blow-Off Heat Flux Sensor. *Applied Thermal Engineering*, Vol. 16, pp. 481-489.

Martins, N., Calisto, H., Afgan, N., Leontiev, A. I. (2006); The transient transpiration heat flux meter. *Applied Thermal Engineering*, Vol. 26, pp. 1552-1555.

Martins, N., Hit, S., Calisto, H., Afgan, N. (2006); The Transient Transpiration Radiometer – Analysis and Parameter Selection. *Applied Thermal Engineering*, Vol. 26, pp. 2247-2254.

Martins, N., Calisto, H. (2006); Diagnostic System for Boilers and Furnaces Using CFD Tools and a Neural Network-Based Approach. *7th European Conference on Industrial Furnaces and Boilers*, Porto, Portugal, 18-21 April.

Ogaji, S. O. T., Singh, R. (2003); Advanced engine diagnostics using artificial neural networks. *Applied Soft Computing*, Vol. 3, pp. 259-271.

Romeo, L. M., Gareta, R. (2006); Neural network for evaluating boiler behaviour. *Applied Thermal Engineering*, Vol. 26, pp. 1530–1536.

Sen, M., Yang, K. T. (2000); Application of artificial neural networks and genetic algorithms in thermal engineering, in: CRC Handbook of Thermal Engineering, 620-661.

The MathWorks, Inc. (2004), MATLAB 6.5 Documentation.

Venkatasubramanian, V., Rengaswamy, R., Yin, K., Kavuri, S.N. (2003); A Review of process fault detection and diagnosis - Part I: Quantitative model-based methods. *Computers & Chemical Engineering*, Vol. 27, pp. 293-311.

Venkatasubramanian, V., Rengaswamy, R., Kavuri, S.N. (2003); A Review of process fault detection and diagnosis - Part II: Qualitative models and search strategies. *Computers & Chemical Engineering*, Vol. 27, pp. 313-326.

Venkatasubramanian, V., Rengaswamy, R., Kavuri, S.N., Yin, K. (2003); A Review of process fault detection and diagnosis - Part III: Process history based methods. *Computers & Chemical Engineering*, Vol. 27, pp. 327-346.