

FAULT DIAGNOSIS IN CHEMICAL PLANTS
INTEGRATED TO THE INFORMATION SYSTEM

Thesis
presented by
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A Silvia
To Silvia

A mis padres
To my parents

A todos los que hacen las cosas con amor
A tots els que fan les coses amb amor
To the people who make the things with love

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Contents

Acknowledgements.....	i
Agradecimientos (Acknowledgements, in Spanish).....	iii
Contents.....	v
Figures index.....	xi
Tables index.....	xvii
Summary.....	xix
Resumen (Summary, in Spanish).....	xxiii
1. Introduction.....	1
1.1. Abnormal situation management in chemical plants. The role of operators.....	2
1.2. Fault diagnosis in batch chemical plants.....	4
1.3. Terminology.....	4
1.4. Fault diagnosis system requirements.....	5
2. Objectives.....	7
3. State of the art.....	9
3.1. Historical based methods.....	9

3.1.1. Artificial Neural Networks.....	10
3.1.2. Statistical techniques.....	12
3.1.3. Trend Analysis.....	15
3.2. Knowledge-based methods.....	18
3.2.1. Observer based methods.....	18
3.2.2. Assumption-based methods.....	20
3.2.3. Signed Directed Graphs.....	21
3.2.4. Fuzzy logic expert systems.....	24
3.3. Combinations.....	24
3.4. Fault Diagnosis in batch processes.....	26
Acronyms / Notation.....	32
4. Tools and techniques.....	33
4.1. Artificial Neural Networks.....	33
4.1.1. Types of Artificial Neural Networks.....	36
4.1.2. Auto-associative neural network architecture and training.....	40
4.2. Fuzzy Logic.....	41
4.2.1. Definitions.....	42
4.2.2. Fuzzy logic systems.....	44
4.2.3. Types of fuzzy logic systems.....	46
4.3. HAZOP analysis.....	47
4.3.1. Introduction.....	47
4.3.2. The choice of the HAZOP analysis.....	48
4.3.3. HAZOP analysis for continuous processes.....	50
4.3.4. HAZOP for batch processes.....	51
4.4. Signal processing using wavelets.....	52
4.5. Conclusions.....	56

Acronyms / Notation.....	57
Greek symbols.....	58
5. Methodology.....	59
5.1. Proposed Fault Diagnosis System.....	60
5.1.1. The use of a combined approach for the FDS.....	60
5.1.2. General structure of the proposed Neuro-fuzzy FDS.....	61
5.2. Step by step methodology.....	62
5.3. Performance Index.....	70
5.4. Artificial Neural Network implementation.....	72
5.4.1. ANN training using the profiles of variables directly.....	72
5.4.2. ANN training using the fault patterns composed by signals features.....	75
5.4.3. Fault in sensors diagnosis using Autoassociative ANN.....	76
5.4.4. Recommendations for successful ANN implementation.....	81
5.5. Fuzzy logic development.....	81
5.5.1. Generation of if-then rules from HAZOP analysis.....	82
5.5.2. Generation of if-then rules from ANN performance experience.....	85
5.5.3. Adjustment of the membership functions.....	85
5.6. On line implementation of the FDS.....	86
5.7. Determination of the information to be sent to other levels.....	90
5.8. Conclusions.....	91
Acronyms / Notation.....	92
Greek symbols.....	93
6. Case studies.....	95
6.1. Academic scenarios.....	95
6.1.1. Plant with recycle.....	95

6.1.2. Batch reactor.....	99
6.2. Pilot Plant scenarios.....	101
6.2.1. Fluidised coal gasifier.....	101
6.2.2. Fed-batch reactor.....	104
6.2.3. Multipurpose batch chemical plant.....	107
6.3. Industrial scenarios.....	108
6.3.1. Sugar cane refineries.....	109
6.3.2. Petrochemical Plant.....	113
7. Results and discussion.....	115
7.1. Plant with recycle.....	115
7.1.1. Implementation of the proposed combination.....	115
7.1.2. Comparison of ANNs' performance.....	120
7.1.3. Faults in sensors.....	124
7.2. Batch Reactor.....	127
7.2.1. ANN training.....	127
7.2.2. Fuzzy logic system.....	130
7.2.3. Results.....	132
7.2.4. Types of Fuzzy Logic Systems.....	139
7.3. Fluidised bed coal gasifier.....	142
7.3.1. Process faults.....	142
7.3.2. ANN training.....	142
7.3.3. Comparison against Principal Component Analysis (PCA).....	146
7.3.4. Discussion.....	147
7.3.5. Faults in sensors.....	148
7.4. Batch plant at pilot plant scale.....	151
7.4.1. Fed-batch Reactor.....	151

7.4.2. Multipurpose batch chemical plant.....	155
Acronyms / Notation.....	159
8. Industrial applications.....	161
8.1. CACSA Sugar cane refinery.....	161
8.1.1. Sources of information.....	162
8.1.2. ANN development.....	164
8.1.3. FLS development.....	168
8.1.4. Check list for the operators.....	169
8.1.5. Discussion.....	174
8.2. CAICC sugar cane refinery.....	175
8.3. Petrochemical plant.....	179
8.3.1. Historical data.....	179
8.3.2. Plant model.....	179
8.3.3. HAZOP analysis.....	180
8.3.4. Implementation results.....	182
8.3.5. Discussion.....	184
8.4. Conclusions.....	184
Acronyms / Notation / Greek symbols.....	186
9. Conclusions.....	187
Nomenclature.....	191
Acronyms.....	191
Notation.....	192
Greek symbols.....	193
Bibliography.....	195

Annex A.....	205
CACSA HAZOP analysis.....	206
CAICC HAZOP analysis.....	214
Annex B: Publications and Conferences.....	217

Figures Index

<i>Figure 1.1. Operational goals according to plant status.....</i>	<i>3</i>
<i>Figure 3.1. Ways of using ANNs for Fault Diagnosis.....</i>	<i>11</i>
<i>Figure 3.2. Example of a Q plot. Fault detected at time 15 (minutes).....</i>	<i>14</i>
<i>Figure 3.3. Example of a T^2 plot. Fault detected at time 15 (min.).....</i>	<i>14</i>
<i>Figure 3.4. Fundamental elements, primitives, the language for sensor trends.....</i>	<i>16</i>
<i>Figure 3.5. Qualitative Trend Analysis framework.....</i>	<i>17</i>
<i>Figure 3.6. General Observer based method scheme.....</i>	<i>19</i>
<i>Figure 3.7. Mixing tee example for model equation formulation.....</i>	<i>21</i>
<i>Figure 3.8. Diagnostic model processor, an Assumption Based Method.....</i>	<i>21</i>
<i>Figure 3.9. Two tanks in series and the corresponding signed digraph.....</i>	<i>22</i>
<i>Figure 3.10. The cause-effect graph for the pattern of Table 3. 1.....</i>	<i>22</i>
<i>Figure 3.11. Blackboard architecture for a hybrid framework.....</i>	<i>25</i>
<i>Figure 3.12. Arrangement and decomposition of a three-way array by MPCA.....</i>	<i>27</i>
<i>Figure 3.13. % Contribution to the SPE value for an abnormal batch.....</i>	<i>29</i>
<i>Figure 3.14. Hybrid modular hierarchical architecture for FD in batch plants.....</i>	<i>29</i>
<i>Figure 4.1. Processing node of an Artificial Neural Network.....</i>	<i>34</i>
<i>Figure 4.2. An example of a Multilayer Perceptron neural network.....</i>	<i>35</i>
<i>Figure 4.3. Backpropagation Network.....</i>	<i>38</i>

<i>Figure 4.4. An example of a self organizing map with 25 active nodes.....</i>	<i>39</i>
<i>Figure 4.5. Autoassociative Neural Network.....</i>	<i>41</i>
<i>Figure 4.6. Example of a fuzzy set.....</i>	<i>42</i>
<i>Figure 4.7. Fuzzy reasoning for multiple rules with multiple antecedents.....</i>	<i>44</i>
<i>Figure 4.8. Fuzzy Logic System scheme.....</i>	<i>45</i>
<i>Figure 4.9. Defuzzification methods.....</i>	<i>46</i>
<i>Figure 4.10. Logic diagram of a HAZOP analysis of continuous process.....</i>	<i>49</i>
<i>Figure 4.11. Logic diagram of HAZOP for batch processes.....</i>	<i>52</i>
<i>Figure 4.12. Multiresolution analysis.....</i>	<i>54</i>
<i>Figure 4.13. Wavelet decomposition using Daubechies-6 wavelet.....</i>	<i>55</i>
<i>Figure 5.1. Abnormal situation management scheme.....</i>	<i>59</i>
<i>Figure 5.2. Proposed Fault Diagnosis System (Detailed scheme).....</i>	<i>60</i>
<i>Figure 5.3. Proposed Fault Diagnosis System (General scheme).....</i>	<i>62</i>
<i>Figure 5.4. Flowsheet of the proposed methodology to design the FDS.....</i>	<i>67</i>
<i>Figure 5.5. Systematic definition of the set of faults.....</i>	<i>68</i>
<i>Figure 5.6. Generation of fault patterns.....</i>	<i>69</i>
<i>Figure 5.7. Definition of parameters used in the evaluation of the performance of the fault diagnosis system (steady-state processes).....</i>	<i>71</i>
<i>Figure 5.8. Definition of parameters used in the evaluation of the performance of the fault diagnosis system (batch processes).....</i>	<i>71</i>
<i>Figure 5.9. ANN implementation using directly the measured variables a)Continuous processes; b) Batch processes; c) With a moving window for complex dynamics.....</i>	<i>73</i>
<i>Figure 5.10. ANN training using the measurements from the plant directly (continuous plant).....</i>	<i>74</i>
<i>Figure 5.11. Extrema determination.....</i>	<i>75</i>
<i>Figure 5.12. Signal preprocessing to generate the fault patterns used in the ANN training.....</i>	<i>76</i>
<i>Figure 5.13. Proposed algorithm to isolate the faulty sensor from the Auto-associative Artificial Neural Network's response.....</i>	<i>79</i>

Figure 5.14. Fault in sensor 1 at time 100. a) SPE_j of each sensor; b) $SPE_{js}\%$ of each sensor.....	80
Figure 5.15. Example: Some stream lines in a chemical plant.....	82
Figure 5.16. Generation of if then rules from HAZOP analysis.....	84
Figure 5.17. Input membership functions adjustment.....	86
Figure 5.18. Main program for on line implementation of the FDS.....	87
Figure 5.19. ANN output determination, using a BPN.....	88
Figure 5.20. FLS algorithm for on line implementation of the proposed FDS.....	89
Figure 5.21. A simple example of the application of the FLS algorithm.....	90
Figure 6.1. Chemical plant with a recycle stream.....	98
Figure 6.2. Masking knowledge by the control system.....	99
Figure 6.3. Batch reactor scheme.....	100
Figure 6.4. Profiles of measured and inferred variables under normal operating conditions.....	101
Figure 6.5. Fluidised bed Coal gasifier.....	102
Figure 6.6. Simplified diagram of the monitoring system.....	103
Figure 6.7. Scheme of the fed batch reactor as it appears in the user interface.....	105
Figure 6.8. Profiles of tank levels during reactant A feeding.....	105
Figure 6.9. Profiles of inferred concentrations of reactants.....	106
Figure 6.10. Profiles of direct and indirect measurements from the plant under normal operating conditions.....	106
Figure 6.11. Flowsheet of the multipurpose chemical plant.....	107
Figure 6.12. Gantt chart performing two batches.....	108
Figure 6.13. CACSA - Sugar cane refinery flowsheet.....	110
Figure 6.14. CACSA monitoring system.....	111
Figure 6.15. Scheme of a section of the Refinery plant (CAICC).....	112
Figure 6.16. Plant flow sheet.....	114
Figure 7.1. ANN approach response (Fault F3).....	117

<i>Figure 7.2. Fault Diagnosis System response (Fault F1).....</i>	<i>118</i>
<i>Figure 7.3. BPNs; a) Performance, b) False diagnosis.....</i>	<i>121</i>
<i>Figure 7.4. RBFNs; a) Performance, b) False diagnosis.....</i>	<i>122</i>
<i>Figure 7.5. SOMs; a) Performance, b) False diagnosis.....</i>	<i>123</i>
<i>Figure 7.6. Performance of the different kinds of ANNs taking into account the false diagnosis and the resolution.....</i>	<i>124</i>
<i>Figure 7.7. Profiles of measured variables.....</i>	<i>128</i>
<i>Figure 7.8. Wavelet extrema analysis of detail at scale 5.....</i>	<i>129</i>
<i>Figure 7.9. Initial steam control valve leakage, responses of a) ANN, b) FDS.....</i>	<i>134</i>
<i>Figure 7.10. Water control valve leakage at time 100, ANN and FDS responses.....</i>	<i>134</i>
<i>Figure 7.11. Fouling of the reactor temp. probe, responses of a) ANN, b) FDS.....</i>	<i>135</i>
<i>Figure 7.12. Fouling of the reactor jacket, a) ANN response, b) FDS response.....</i>	<i>135</i>
<i>Figure 7.13. Fouling of reactor walls, a)ANN response, b) FDS response.....</i>	<i>136</i>
<i>Figure 7.14. Incorrect master gain (higher) at time 200, ANN and FDS responses....</i>	<i>136</i>
<i>Figure 7.15. Incorrect slave gain (lower) at time 100, ANN and FDS responses.....</i>	<i>137</i>
<i>Figure 7.16. SPE plot for a normal batch, on-line MPCA.....</i>	<i>138</i>
<i>Figure 7.17. SPE plot for a batch with the initial problem of leaking in the steam control valve, Fault 1.....</i>	<i>138</i>
<i>Figure 7.18. Fault 1: Melting of ashes at the reactor bottom and the subsequent obstruction in the air distributor, at time 102 min.....</i>	<i>143</i>
<i>Figure 7.19. Fault 2: High flow-rate of water is fed to the reactor at time 62 min.....</i>	<i>143</i>
<i>Figure 7.20. Fault 1 at 102 min.; a)ANN and b) FDS responses.....</i>	<i>144</i>
<i>Figure 7.21. Fault 2 at 62 min.; a) ANN and b) FDS responses.....</i>	<i>145</i>
<i>Figure 7.22. Fault detection by conventional PCA; Fault 1 at time 102 min.....</i>	<i>146</i>
<i>Figure 7.23. Fault detection by conventional PCA; Fault 2 at time 62 min.....</i>	<i>147</i>
<i>Figure 7.24. Fault in sensor T1. Detection using NLPCA by an AANN.....</i>	<i>149</i>
<i>Figure 7.25. Fault in sensor T1. Detection using conventional PCA.....</i>	<i>149</i>
<i>Figure 7.26. Fault in sensor %CO2. Detection using NLPCA by AANN.....</i>	<i>150</i>

<i>Figure 7.27. Fault in sensor %CO₂. Detection using conventional PCA.....</i>	<i>150</i>
<i>Figure 7.28. Responses for a batch run with the initial problem of low reactant concentration in the feed; a) ANN; b) FDS.....</i>	<i>152</i>
<i>Figure 7.29. Monitoring chart with its 95% and 99% control limits for a batch run with the initial problem of low reactant concentration in the feed.....</i>	<i>154</i>
<i>Figure 7.30. Tank levels profiles for Normal batch, Abnormal batch without FDS and Abnormal batch with FDS support.....</i>	<i>156</i>
<i>Figure 7.31. Comparison of Abnormal situation management: a) Initial schedule, b) Schedule performed without the FDS support and c) Schedule with FDS and reactive scheduling.....</i>	<i>157</i>
<i>Figure 8.1. P&ID of the dissolution station.....</i>	<i>162</i>
<i>Figure 8.2. ANN scheme.....</i>	<i>165</i>
<i>Figure 8.3. ANN training.....</i>	<i>165</i>
<i>Figure 8.4. Example of Fault 1 occurrence; a) Steam pressure and vacuum profiles. b) ANN response.....</i>	<i>166</i>
<i>Figure 8.5. Example of Fault 2 occurrence; a) Steam pressure and vacuum profiles. b) ANN response.....</i>	<i>167</i>
<i>Figure 8.6. GUI of the subFLS for the diagnosis of Fault 1.....</i>	<i>170</i>
<i>Figure 8.7. Membership function plots for the input steam pressure.....</i>	<i>171</i>
<i>Figure 8.8. Set of rules of the sub-FLS for Fault 1 diagnosis.....</i>	<i>171</i>
<i>Figure 8.9. Fuzzy reasoning when Fault 1 is simulated.....</i>	<i>172</i>
<i>Figure 8.10. FDS response during May23th 1998. Fault 1 occurred several times....</i>	<i>173</i>
<i>Figure 8.11. FDS response during May23th, 1998. Fault 2 diagnosed at time 9.15...173</i>	
<i>Figure 8.12. Fuzzy reasoning when Fault "Excess of steam to the refinery" has been simulated.....</i>	<i>177</i>
<i>Figure 8.13. GUI of the FDS support for operators at CAICC plant.....</i>	<i>178</i>
<i>Figure 8.14. PCA plot indicating a plant upset.....</i>	<i>181</i>
<i>Figure 8.15. Neural model response to the identified upset.....</i>	<i>181</i>
<i>Figure 8.16. Extrema Determination from wavelet decomposition of signal Feed Flow rate to the stripper.....</i>	<i>183</i>

<i>Figure 8.17. HYSYS.Plant Graphical user interface. Fault "High Hot oil to Reboiler" simulated.....</i>	<i>185</i>
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Tables index

<i>Table 3.1. A possible pattern for two tank in series.....</i>	<i>22</i>
<i>Table 3.2. An example of a constraint representing incomplete knowledge of the process state for the example of the two tanks in series.....</i>	<i>23</i>
<i>Table 3.3. Classification of FD methods and their attributes.....</i>	<i>25</i>
<i>Table 4.1. HAZOP Guidewords.....</i>	<i>50</i>
<i>Table 5.1. Scheme of the set of rules.....</i>	<i>62</i>
<i>Table 5.2. A HAZOP analysis of a stream line in a batch process.....</i>	<i>83</i>
<i>Table 5.3. Information to be sent to other levels.....</i>	<i>91</i>
<i>Table 6.1. Steady state design.....</i>	<i>98</i>
<i>Table 6.2. List of sensors in the pilot plant. Fluidised bed coal gasifier.....</i>	<i>103</i>
<i>Table 6.3. Operation description.....</i>	<i>108</i>
<i>Table 6.4. Monitoring system.....</i>	<i>110</i>
<i>Table 6.5. Itemised description of the plant equipment and nodes.....</i>	<i>113</i>
<i>Table 7.1. List of simulated faults.....</i>	<i>116</i>
<i>Table 7.2. Time for diagnosis (in minutes).....</i>	<i>119</i>
<i>Table 7.3. Normal condition and bias errors in sensors.....</i>	<i>125</i>
<i>Table 7.4. Performance of auto-associative neural networks.....</i>	<i>126</i>
<i>Table 7.5. List of suspected faults.....</i>	<i>128</i>
<i>Table 7.6. HAZOP analysis of two steps of the batch reactor.....</i>	<i>130</i>

<i>Table 7.7. Set of if-then rules based on process knowledge. a) Reactor heating operation; b) Reactor cooling operation.....</i>	<i>131</i>
<i>Table 7.8. Cases used for testing the FDS and times for diagnosis.....</i>	<i>133</i>
<i>Table 7.9. Cases where the FLSs have been tested for comparison purposes.....</i>	<i>139</i>
<i>Table 7.10. FLSs considered.....</i>	<i>141</i>
<i>Table 7.11. Performance of the FLSs (%P).....</i>	<i>141</i>
<i>Table 7.12. Time for diagnosis (in minutes) and %P.....</i>	<i>147</i>
<i>Table 7.13. Isolation of faulty sensors.....</i>	<i>148</i>
<i>Table 7.14. FDS performance.....</i>	<i>153</i>
<i>Table 7.15. Energy consumption comparison.....</i>	<i>158</i>
<i>Table 7.16. Performance comparison -makespan-.....</i>	<i>158</i>
<i>Table 8.1. Partial HAZOP analysis (dissolution station).....</i>	<i>163</i>
<i>Table 8.2. Partial HAZOP analysis of Boiling Station.....</i>	<i>164</i>
<i>Table 8.3. Proposed checklist for the operators.....</i>	<i>170</i>
<i>Table 8.4. Partial scheme of HAZOP analysis - CAICC- "Raw sugar mingled".....</i>	<i>176</i>
<i>Table 8.5. Fragments of the HAZOP analysis.....</i>	<i>180</i>

Summary

The growing necessities of improvements in product quality and process productivity, plus the environmental and safety requirements, have motivated that the chemical plant designs and their control systems are very complex. This high complexity makes necessary the assistance to plant operators for fault diagnosis and the following decision-making in order to manage abnormal situations (Chapter 1, Introduction).

The pretended contribution of this thesis deals with the implementation of a fault diagnosis system in chemical plants integrated to the monitoring, management and control system (Chapter 2, Objectives).

First, the state of the art is presented (Chapter 3), describing the existing methods for fault diagnosis. Fault diagnosis methods can be classified in three main groups: historical based, knowledge-based and combination of both. The use of a wise combination where methods are adapted to each other in order to improve the advantages and to reduce the drawbacks seems to be the best option. Furthermore, these methods overcome the so called hybrid systems which consist in the implementation of some different methods (and then deciding among the different obtained responses) due to the difficulties related to the implementation of each individual methodology. Also, a special overview of the fault diagnosis methods for batch processes is presented. There exist very few methods due to the high complexity involved. Moreover, it has to be taken into account that the information provided by the fault diagnosis system will be utilised by other levels in the information system as the scheduling system.

The fault diagnosis system that is introduced in this thesis consists in a combination of a pattern recognition approach based on artificial neural networks and an inference

system based on fuzzy logic. Therefore, a brief overview about the concepts of neural network and fuzzy logic technologies is introduced (Chapter 4, Tools and techniques). A summary about Hazard and Operability analysis (HAZOP) and the signal pre-processing using wavelets is also included because such techniques are utilised in the design and implementation of the proposed fault diagnosis system.

The general structure of the fault diagnosis system is shown in Figure 5.3 (Chapter 5, Methodology). The fuzzy logic system complements the artificial neural network in a block oriented configuration. The inputs to the system are the direct or indirect measurements from the plant and the output consists in a signal for each fault (0: no fault; 1: fault).

The information needed to develop the fault diagnosis system includes the historical data, the hazard and operability study and the model of the chemical plant. First, the possible faults with high importance are defined, according to the historical data and the hazard analysis, taking into account the economic impact and the frequency of them. The artificial neural network is trained with historical data of faults occurred in the past, with the aim of recognising the respective patterns. In the case that the corresponding historical data are not available, for example due to the no occurrence of the fault, the patterns are obtained through simulation, using the plant model. The fuzzy logic system contains a set of if-then rules that can be of two types: those based in the process knowledge, by the hazard analysis or by the experience with simulation, and those based on the experience with the use of an artificial neural network, previously trained. Other novel aspect is the possibility of artificial neural network training by using signals features that are extracted by its pre-processing using wavelets. This alternative allows a higher fault diagnosis system performance in batch and complex continuous chemical plants.

In order to optimise the parameters of the components of the fault diagnosis system, a performance index is proposed, Equation (5.1) and Figures 5.7 and 5.8, which takes into account the time required for a correct diagnosis. The performance index is also utilised to compare the proposed fault diagnosis system against other methods.

The selection of the type of artificial neural network is not a critical aspect for the success of the system implementation. Nevertheless, in the performed applications the following neural networks have been preferred: a probabilistic neural network to classify fault patterns given by features extracted by signal pre-processing using wavelets, a radial basis function network for the case of training with variables' profiles directly, except for large amount of training data where the backpropagation network is

chosen, and auto -associative neural networks for the special case of fault diagnosis in sensors.

The on-line implementation of the fault diagnosis system is performed with the algorithm shown in Figure 5.18 and the subprograms shown in Figures 5.19 and 5.20.

The signals provided by the fault diagnosis system can be used by the scheduling system to update the schedule in the most effective way, by the control system to take automated control actions and by plant's operators as support for decision-making. The basis of the translation of the system output for its utilisation at other levels in the information system have been settled. The proposed strategy is based on the hazard and operability analysis.

The proposed system is the result of successive improvements, by working with different case studies. The academic scenarios correspond to a continuous chemical plant with a recycle stream and a batch reactor. The pilot plant scale cases correspond to scenarios built at UPC: a reactor gasifier, a fed-batch reactor and a multipurpose batch chemical plant. The industrial scenarios correspond to two sugar refineries and a sector of a petrochemical plant. A description of the case studies is done in Chapter 6 (Case studies).

Different aspects of the proposed methodology are illustrated by the implementation of the proposed fault diagnosis system in different case studies (Chapter 7, Results and discussion).

In the case of the chemical plant with recycle, the advantages of the proposed system with respect to a neural network or an expert system working alone, are shown. Such advantages include the speed of diagnosis, the exactness of multiple fault diagnosis and the no existence of cases of false diagnosis.

In the case of the batch reactor, the use of fault patterns based on the extracted features by signal pre-processing using wavelets for artificial neural network training is shown. Furthermore, the generation of if-then rules for the fuzzy logic system, based on the hazard analysis is illustrated, too. A comparison against a statistical method is done and a better performance of the proposed system is observed in relation to its capacity to isolate faults.

Implementation in the case of the gasifier, using real data, allows to show that the system has better performance than statistical techniques. The system implementation is also illustrated in the case of semi-batch and batch plants. The translation of the

system output for its utilisation at other levels in information system is treated in these scenarios.

Implementation of the proposed fault diagnosis system has been tested and validated in three industrial cases (Chapter 8, Industrial applications). In the first case, one of the sugar cane refineries, results are shown for the application of the fault diagnosis system in the sector of Boiling and Crystallisation, where problems derived from the fluctuations in the steam supply and vacuum generation affect directly the quality product. A method is proposed to update the system with the participation of plants' operators (Table 8.3). In the second case, a sector of other sugar refinery, an application of the fault diagnosis system is presented with the additional difficulty of the lack of on-line measurements from the plant. A system has been given to the company to assist plant's operators for decision-making. Such a tool allows them diagnosing possible faults, after performing some observations and measurements from the plant in "off line" mode. Finally, the system implementation is shown in a sector of a petrochemical plant. The proposed fault diagnosis system is able to adequately diagnose fluctuations in the flowrates of hot oil to the reboilers of the distillation columns. Furthermore, it is possible to take advantage of some commercial softwares that are familiar to plant engineers.

The simplicity of the development and the flexible strategy of implementation of the proposed fault diagnosis system give a promising future to the presented technology (Chapter 9, Conclusions).

Resumen *(Summary, in Spanish)*

Las necesidades crecientes de mejorar la calidad de los productos y la rentabilidad de los procesos, sumado a las exigencias de protección del medio ambiente y la seguridad de operación, han motivado que los diseños de plantas químicas y sus sistemas de control sean muy complejos. Esta elevada complejidad hace necesaria la asistencia a los operadores en la diagnosis de fallos y la consiguiente toma de decisiones para gestionar las situaciones anormales (Capítulo 1, Introducción).

La contribución que se pretende con esta tesis se refiere a la implantación de un sistema de diagnosis de fallos en plantas químicas completas integrado al sistema de supervisión, gestión y control de la producción (Capítulo 2, Objetivos).

En primer lugar se presenta un resumen del estado del arte (Capítulo 3), describiendo los métodos existentes para la diagnosis de fallos. Los mismos se pueden clasificar en tres grupos principales: los basados en datos históricos, los basados en el conocimiento del proceso y combinaciones de ambos. El uso de una combinación inteligente en la que los métodos se adaptan uno al otro para mejorar las ventajas individuales y reducir los puntos débiles parece ser la mejor opción. Además, estos sistemas superan a los llamados sistemas híbridos que consisten en implementar varios métodos diferentes y luego decidir entre los distintos resultados obtenidos, debido a las dificultades de implementación de cada técnica individual. También se presenta una revisión especial de los métodos actuales para la diagnosis de fallos en plantas discontinuas. Existen muy pocos métodos para estos casos dada la elevada complejidad de implantación. Además, se debe tener en cuenta que la información que suministre el sistema de diagnosis será utilizado a otros niveles del sistema informático de la planta como el de programación de la producción.

El sistema de diagnóstico de fallos que se presenta en esta tesis consiste en una combinación de un sistema de reconocimiento de patrones basado en redes neuronales artificiales y un sistema de inferencia basado en la lógica difusa. Se incluye entonces una breve revisión de los conceptos de la tecnología de redes neuronales y la lógica difusa (Capítulo 4, Herramientas y técnicas). Además, se hace un resumen sobre el análisis de riesgo y operabilidad (HAZOP) y el pre-procesamiento de señales usando *wavelets*, ya que estas técnicas se usan en el diseño e implementación del sistema de diagnóstico que se propone.

La estructura general del sistema de diagnóstico de fallos se muestra en la Figura 5.3 (Capítulo 5, Metodología). El sistema de lógica difusa complementa a una red neuronal en una combinación orientada a bloques. La entrada al sistema son las mediciones directas o indirectas de la planta y la salida consiste en una señal para cada fallo (0: no fallo; 1: fallo).

La información necesaria para desarrollar el sistema de diagnóstico incluye los datos históricos, un análisis de riesgo y operabilidad y un modelo de la planta química. Primero se definen los fallos posibles con alta importancia, de acuerdo con los datos históricos y el análisis de riesgo, teniendo en cuenta el impacto económico y la frecuencia de los mismos. La red neuronal se entrena con datos históricos de fallos ocurridos en el pasado, con el objeto de reconocer los patrones respectivos. En el caso de que no se posean los datos históricos de alguno de los fallos, por ejemplo porque nunca hayan ocurrido, se obtienen los patrones mediante la simulación, usando el modelo de la planta. El sistema de lógica difusa contiene un conjunto de reglas si-entonces que pueden ser de dos tipos: las basadas en el conocimiento de la planta, mediante el análisis de riesgo o la experiencia con la simulación, y las basadas en la experiencia con el uso de la red neuronal, previamente entrenada. Otro aspecto novedoso es la posibilidad de entrenar la red neuronal con "características" extraídas de las variables medidas mediante su pre-procesamiento con *wavelets*. Esta variante permite obtener un alto rendimiento del sistema de diagnóstico en plantas químicas discontinuas y continuas complejas.

Para optimizar los parámetros de los componentes del sistema de diagnóstico se propone un índice de rendimiento, Ecuación (5.1) y Figuras 5.7 y 5.8, que tiene en cuenta el tiempo requerido para una diagnóstico correcta. Además, se utiliza el índice de rendimiento para comparar el sistema propuesto con otros métodos.

La selección del tipo de red neuronal no es un aspecto determinante del éxito del sistema. No obstante, en las aplicaciones realizadas se han preferido las siguientes

redes neuronales: una red neuronal probabilística para clasificar patrones de fallos dados por "características" extraídas mediante el pre-procesamiento con *wavelets*, una red neuronal con funciones en base radial para el caso del entrenamiento con perfiles de las variables, salvo que los datos de entrenamiento sean cuantiosos, donde se ha elegido una red "backpropagation", y una red auto-asociativa para el caso especial de la diagnosis de fallos en sensores.

La implementación en línea del sistema de diagnosis se realiza con el algoritmo esquematizado en las Figura 5.18 y los subprogramas mostrados en las Figuras 5.19 y 5.20.

Las señales dadas por el sistema de diagnosis pueden ser usadas por el sistema de programación de la producción para actualizar el plan de la manera más efectiva, por el sistema de control para actuar en forma automática y por los operadores de planta como soporte para la toma de decisiones. Se han sentado las bases para la traducción de la salida del sistema de diagnosis para su utilización por los demás niveles del soporte informático. Se usa una estrategia basada en el análisis de riesgo y operabilidad de la planta.

El sistema propuesto es consecuencia de sucesivas mejoras, al trabajar con diferentes casos de estudio. Los escenarios académicos corresponden a una planta química continua con una corriente de reciclaje y un reactor discontinuo. Los casos a escala de planta piloto corresponden a escenarios construidos en la UPC: un reactor de gasificación, un reactor semicontinuo y una planta discontinua multipropósito. Los escenarios industriales corresponden a dos refinerías de azúcar y a un sector de una planta petroquímica. Una descripción de los casos de estudio se realiza en el Capítulo 6 (Casos de estudio).

Distintos aspectos de la metodología propuesta se ilustran mediante la implementación del sistema de diagnosis propuesto en los distintos casos de estudios (Capítulo 7, Resultados y discusión).

En el caso de la planta con reciclaje se muestran las ventajas del sistema propuesto respecto a una red neuronal y a un sistema experto que trabajan por separado. Tales ventajas incluyen la velocidad de diagnosis, la exactitud en la diagnosis de fallos múltiples y la inexistencia de casos de diagnosis falsa. También se muestra una comparación de distintos tipos de redes neuronales y la optimización de sus parámetros, usando el índice de rendimiento propuesto. Además se muestra la aplicación de redes neuronales autoasociativas para diagnosticar fallos en sensores.

En el caso del reactor discontinuo, se muestra el uso de patrones de fallos basados en las "características", extraídas mediante el pre-procesamiento de las mediciones con *wavelets*, para entrenar la red neuronal. Además, se ilustra la generación de reglas si-entonces del sistema de lógica difusa, en base al análisis de riesgo. Se realiza una comparación con un método estadístico, observándose un mejor rendimiento del sistema propuesto en relación con su capacidad de aislar los fallos.

La implementación en el caso del reactor de gasificación, usando datos reales, permite mostrar que el sistema tiene mejor rendimiento que los métodos estadísticos. También se ilustra la implantación del sistema en casos de plantas semicontinuas y discontinuas. La traducción de la salida del sistema para su utilización en otro niveles del sistema informático de la planta se ilustra en estos escenarios.

La implementación del sistema de diagnóstico propuesto se ha verificado y validado en tres casos industriales (Capítulo 8, Aplicaciones industriales). En el primer caso, una refinería de azúcar de caña, se muestra el resultado de la aplicación del sistema de diagnóstico en el sector de "tachos de cocimiento", donde los problemas derivados de las fluctuaciones en el suministro de vapor y en la generación de vacío afectan directamente la calidad del producto final. Se propone un método para actualizar el sistema con la participación de los operadores de planta (Tabla 8.3). En el segundo caso, un sector de otra refinería, se presenta la aplicación del sistema con la dificultad añadida de no contar con mediciones en línea de la planta. Se ha provisto a la compañía de un sistema para la asistencia de los operadores en la toma de decisiones. Tal herramienta les permite diagnosticar posibles fallos, luego de hacer algunas observaciones y mediciones "fuera de línea" de la planta. Finalmente, se muestra la implementación del sistema en un sector de una planta petroquímica. El sistema de diagnóstico propuesto es capaz de diagnosticar adecuadamente las fluctuaciones de caudal de fluido calefactor de los re-hervidores de las columnas de destilación. Además, se pueden aprovechar programas comerciales que resultan familiares a los ingenieros de planta.

La simplicidad del desarrollo y la flexible estrategia de implementación del sistema propuesto auguran un futuro promisorio a la tecnología presentada (Capítulo 9, Conclusiones).