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FAILURE DETECTION AND DIAGNOSIS SYSTEM FOR INSTRUMENTATION IN STEAM GENERATORS HYBRIDIZING FUZZY LOGIC AND SYSTEMATIC METHODOLOGIES

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ABSTRACT

In complex industrial processes, such as a thermo-electric generator, shutdowns of non-scheduled plants occur due to faults in the process and the instruments that make up the automation system, which affects production and become economic losses for the company. Added to this, the need to improve productivity, successful decision making, and the requirement to seek mechanisms to maintain high levels of reliability and safety have created the need to effectively implement modern methodologies of maintenance, reliability and detection and diagnosis systems. In this article, a system of detection and diagnosis of faults is presented, hybridizing diffuse logic and systematic methodologies. Systematic methodologies are used in order to determine which instruments have the greatest impact of failures to optimize human, economic, physical and technological resources when implementing the diffuse detection and fault diagnosis system.

Keywords: fuzzy logic, mode analysis, failure effect, reliability, thermo-electric, instrumentation.

INTRODUCTION

The Reliability Engineering stands out as the theoretical framework in which the automatic methodologies and the systematic methodologies necessary for the optimization of the use of the instruments coexist. The reliability of an instrument is the probability that such instrument operates during a certain period of time without losing its function. The ultimate goal of the Reliability Analysis of the instruments is to change the reactive and corrective activities, not programmed and highly expensive, by planned preventive actions that depend on objective analysis, current situation, and history [1].

On the other hand, the inherent characteristics of fuzzy logic theory make it suitable for the detection and diagnosis of faults. The methodology based on fuzzy logic is based on approximations based on rules that have been proposed as a method capable of performing flexible detection and diagnosis. The rules are described as the relationship between the causes and symptoms of failures. The chosen knowledge that allows the interpretation and diagnosis, is organized in the knowledge base as a set of diffuse conditional states, which relates the results of the test with the conclusions about the conditions of the process or the possible failures [2]-[6].

The objective of this article is to hybridize the automatic fuzzy logic methodology and systematic methodologies such as Pareto diagrams, root cause analysis, fault tree analysis, mode analysis, and design failure effect, risk calculation among others. Where systematic methodologies are a series of tools that allow evaluating the behaviour of the instrument in a systematic way in order to determine the level of operation, the amount of risk and mitigation actions that are required, to ensure its integrity and operational continuity, within the actions of mitigation we have the systems of detection and diagnosis of failures (SDDF) which are a tool that allows to detect and diagnose incipient failures in the components of a system. For this, different automatic methodologies are used. These systems are composed of a data acquisition system and computerized mathematical algorithms, which from the monitored data are able to detect the presence of incipient failures [7].

This article is organized as follows: The first section describes the methodology developed for the selection of the most critical instruments. Then, we apply the systematic methodologies root cause analysis and analysis of the mode and effect of failure to determine the functional failures of the instruments. Then, the fuzzy SDDF is implemented. Finally, the validation is carried out and the conclusions are presented.

SELECTION METHODOLOGY FOR THE INSTRUMENTS THAT PRESENT THE HIGHEST IMPACT OF FAULTS IN THE STEAM GENERATOR

This section describes the steps to follow in order to select the appropriate instruments for the steam generator of a Thermoelectric company, in order to define which instruments, require a fault detection and diagnosis system with the highest priority.

Searching for Initial Information for the Selection of Steam Generator Instruments

For the gathering of information in the field, the following information was collected [8]:

- Manuals of design and operation of the systems and manuals of the equipment belonging to the system. These provide information on the expected function of the systems, how they relate to other systems and what operational limits they possess.
- P&ID´s of the system.

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- Historical records of the equipment that may contain the history of failures and corrective maintenance performed on the equipment. At this point, information was collected about the failures that the boiler system has presented since 2003, which is stored in SAP software.

Construction of the Input Process Output Diagram (I-P-O) and Functional Diagram of the Steam Generator

Consists of diagrams that allow easy visualization of the system, for its later analysis. This stage is carried out through [8], [9]:

- Definition of the process by means of the identification of the main and secondary functions, as specific as possible.
- Establish the process inputs: primary, secondary, service, and control; as well as the outputs of it.
- Define the parameters to which the functions of the system are subject, taking into account the values of the design.

Figure-1 shows the diagram (I-P-O) of the steam generator.

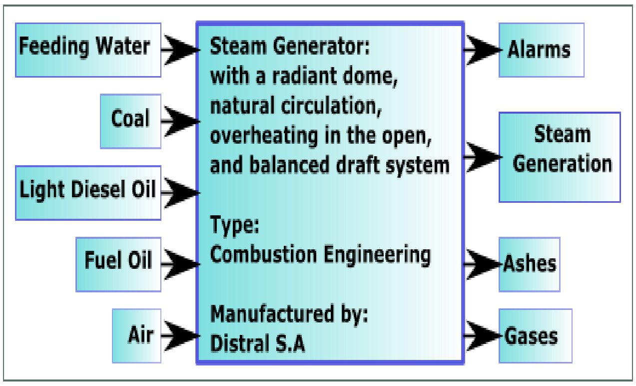

Figure-1. Diagram I-P-O of the steam generator.

Selection of Systems Related to the Steam Generator

Systems with a high number of Corrective Maintenance actions during the last years of operation and/or corrective maintenance costs were selected. For this, the Pareto diagram of the registered corrective maintenances was made, which are listed in Table-1.

Table-1. System failures related to the boiler.

TOTAL SYSTEM FAILURES GRAPHIC			
Systems	**Failures**	**% Failures**	**% Accumulated failures**
SYST 15	580	29,9277606%	29,9277606%
SYST 17	440	22,7038184%	52,6315789%
SYST 07	284	14,6542828%	67,2858617%
SYST 09	213	10,9907121%	78,2765738%
SYST 08	134	6,91434469%	85,1909185%
SYST 01	125	6,4499484%	91,6408669%
SYST 14	112	5,77915377%	97,4200206%
SYST 10	34	1,75438596%	99,1744066%
SYST 13	16	0,8255934%	100%
Total	1938	100%	

In Figure-2 the Pareto diagram of Table-1 is observed, which clearly shows that 78.27% of the faults are caused by systems 15: Air-Gases, 17: Coal Handling, 07: Steam-Boiler Generation, 09: Auxiliary Steam.

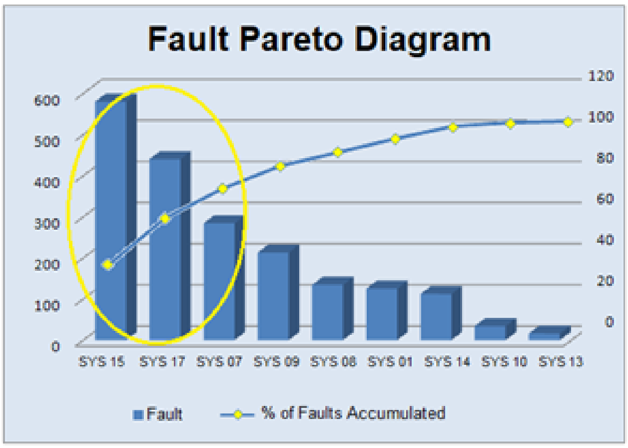

Figure-2. Pareto diagram about system failures related to the boiler.

Next, the Pareto diagram of the costs of corrective maintenance is made, which are listed in Table-2. Figure-3 shows the Pareto diagram in Table-2, which clearly shows that 81.14% of the costs of the corrective maintenance are caused by systems 15: Air-Gases, 17: Coal Handling, 07: Steam-Boiler Generation, 01: Feeding and Condensate Water.

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Table-2. Costs of systems related to the boiler.

TOTAL SYSTEM COST GRAPHIC			
Systems	**COSTS**	**% Cost**	**% Accumulated cost**
S. 17	510.297.999	34,4674391%	34,467439%
S. 15	293.627.081	19,8326734%	54,300112%
S. 07	249.685.038	16,8646631%	71,164775%
S. 01	147.806.519	9,98340618%	81,148181%
S. 09	112.356.437	7,58897479%	88,737156%
S. 08	83.648.985	5,64996591%	94,38712%
S. 14	56.230.832	3,79804111%	98,185163%
S. 10	22.399.496	1,5129459%	99,698109%
S. 13	4.469.555	0,30189049%	100%
Total.	1.480.521.942	100%	

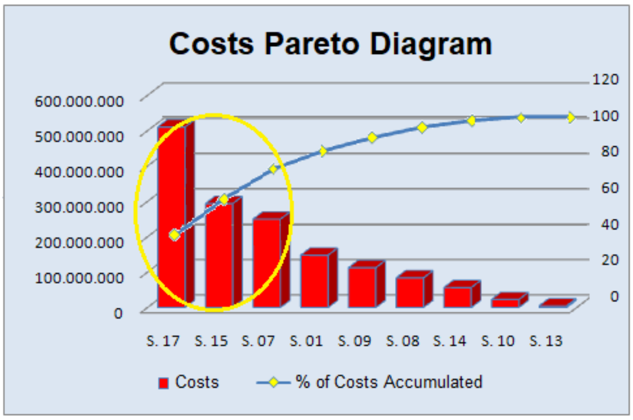

Figure-3. Pareto diagram about the costs of systems related to the boiler.

Finally, the correlation between Figures-2 and 3 is made as shown in Figure-4.

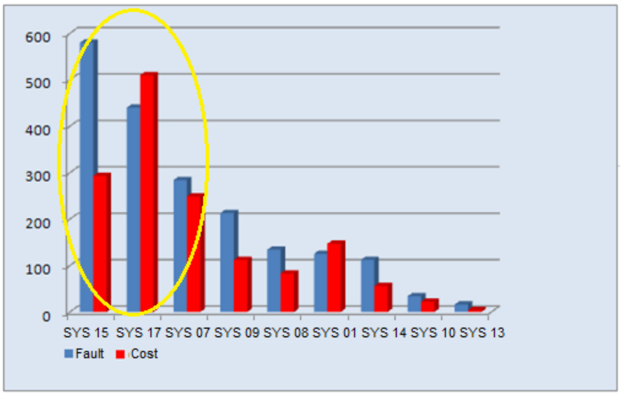

Figure-4. Pareto diagram about costs vs. failures of subsystems related to the boiler.

By performing the three previous steps it was possible to analyze that the systems that contribute to the greatest number of failures that generate corrective maintenance and the highest repair costs are the systems: 15, 17, 07. System 15 will not be taken into account because. The equipment with the most presence of faults and costs was the electrostatic precipitator, which was changed in a technological renovation. And System 17 will not be taken into account because the teams that presented the greatest number of faults are the sprayers which escape from this study. Therefore, system 07 is selected.

Performing the same procedure described above for system 07, it was obtained that the subsystems with the greatest number of corrective maintenance and higher repair costs are the dome (07PP0DK) and the final superheater (07PP0SZ). Therefore, these will be selected to continue with the application of the methodology.

List of instruments, Narratives and Dome Control Diagrams

To obtain the list of instruments, an inventory was made of all the instruments belonging to the dome and the final superheater with their respective identification codes. With respect to the narratives, the security narrative of the dome is shown as an example. Exactly the same is done for the narratives of the process and control.

Narrative of Dome Security: The dome and the superheater may be subjected to pressures greater than the design, with the consequent risk of explosion, and may cause serious consequences for both people and nearby facilities. In order to prevent this risk, safety valves are installed in these devices, which allow, by means of the discharge of the contained fluid, to relieve the excess pressure. In the thermal-electric company studied, the dome has three safety valves; PSV-1T located on the right-side dome, PSV-2T located on the right-side dome and PSV-3T located on the left side dome.

Calculation of Risk in Instruments

The risk is a measure of economic losses, environmental damage or damage to human beings. Risk

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R (t) is a probabilistic term. Mathematically, it is calculated with the Eqn. (1) [10]-[12].

$$R(t) = P(t) * Consequences \quad (1)$$

The risk calculation involves the estimation of the Probability of Faults P(t) and/or Reliability (R). Figure-5 shows the decomposition of the indicator "risk" in its fundamental components. It shows clearly that, to calculate the risk, two ways must be established: one for the calculation of the reliability and/or the probability of failures, based on the history of failures or based on the condition; and another for the calculation of the consequences [11].

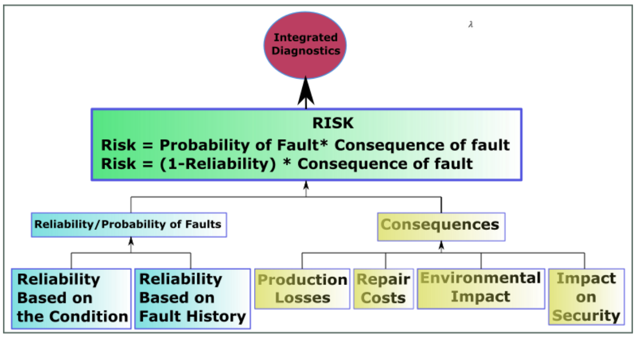

Figure-5. Decomposition of the "risk" indicator.

The failure probability is calculated with the Eqn. (2).

$$P(t) = 1 - R \quad (2)$$

Where R is given by the Eqn. (3).

$$R = e^{-\lambda t} \quad (3)$$

We have that: λ It is a constant that ε [0, + ∞], and it is defined as the failure rate of Instrument i, and it is calculated with the Eqn. (4) [13].

$$\lambda = 1/MTTF \quad (4)$$

MTTF: is the Mean Time to Failure and is given by the Eqn. (5).

$$MTTF = \frac{\sum_{i=1}^{N} TTF}{N} \quad (5)$$

Where TTF: is the time to fail or time in service of instrument *i*.

N is the number of failures of the instrument *i*.

t is the total time of the system.

i is an integer that goes from 1 to n.

Then, the calculation of P (t) is performed for the instruments of each of the selected subsystems. This calculation is based on fault history.

Table-3 shows an example of the historical data collected, which shows the equipment that failed the date and the costs of the failure. With the dates of the failures, we calculate the TTF, applying Eqn. (5) we calculate MTTF, applying Eqn.(4) we calculate λ, with the Eqn.(3) we calculate R, finally, with the Eqn.(2) we calculate P (t).

Table-3. Historical data collected.

Denomin.	Real.cst.tot.	Ref. date
PSV-2T	136.326	29.06.2014
DPV-1	43.680	28.06.2014
DPV-2	958.049	05.08.2015
PSV-1T	1.981.214	12.05.2016
PSV-3T	1.981.214	12.05.2016

Once the calculation of the failure probability is analyzed, the estimation of the consequences is analyzed. These are determined by applying the "Total Business Impact" model developed by John Woodhouse [11], [14]. This model divides the consequences associated with a particular failure into four broad categories: Production losses, repair costs, environmental impact, and safety impact, as can be seen in Figure-6.

- **Loss of Production (L-Pr):** In this step, production losses due to time out of service are estimated using Eqn. (6). Where *PP* is the product price ($ / Unit), *FR* is the flow reduction (Unit/ Hr) and *TTR*, the time to repair (Hrs):

$$L - Pr = PP * RF * TTR \quad (6)$$

- **Repair Costs (R-C):** The distribution of repair costs must include the spectrum of all possible costs, which vary depending on the severity of the failure.
- **Environmental impact (EI) and impact on security (IS):** The distributions of these impacts, in most cases, it is difficult to build, since it is not easy to find data and fundamentally, they need to be built based on the opinion of experts to through brainstorms of unstructured interviews.

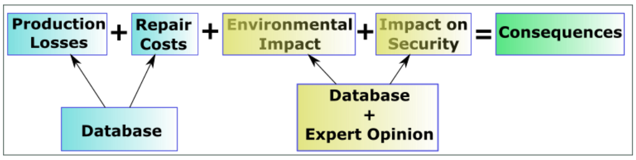

Figure-6. Total impact model in the business.

For the calculation of the consequence, as shown in Figure-6, it is necessary to calculate the production losses, the repair costs, the environmental damage, as an example in Table-4 it is shown how the repair costs were calculated. For the impact on production, environmental and safety is done exactly the same. Once calculated *P(t)* and the consequence (Cons) we calculate the risk as shown in Table-4.

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Table-4. Costs in millions of Colombian pesos.

Millions of pesos	Score
Less than 2.5	1
Between 2.5 and 5	2
Between 5 and 7.5	3
Between 7.5 and 10	4
Between 10 and 12.5	5
Between 12.5 and 15	6
Between 15 and 17.5	7
Between 17.5 and 20	8
Between 20 and 22.5	9
More than 22.5	10

Selection of the Instruments that Require the Application of Fault Detection and Diagnosis Systems with the Highest Priority

Analyzing the risk results by means of Pareto diagrams, see Figure-7 it was determined that the most critical instruments are the PSV-1T, PSV-2T and PSV-3T valves in the dome and the PSV-1E and PSV-1S valves in the final superheater. Therefore, these are the instruments that most urgently require the implementation of fault detection and diagnosis systems in the steam generator of the Thermo-Electric company in question.

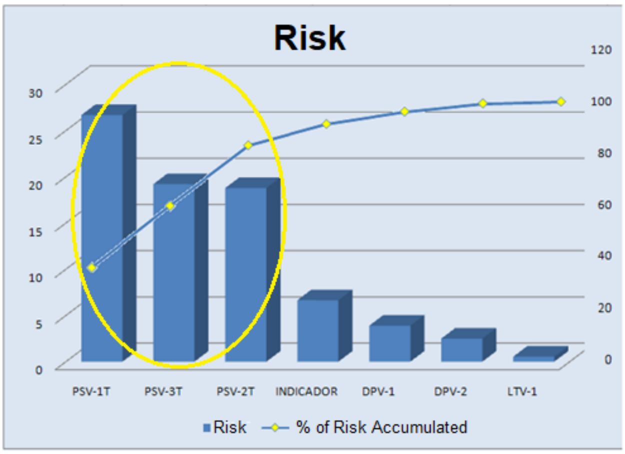

Figure-7. Pareto diagram of the risk of dome instruments.

ROOT CAUSE ANALYSIS AND ANALYSIS OF THE MODE AND FAILURE EFFECT

Once the most critical instruments have been selected, the functional failures are determined. These are obtained through the root cause analysis and cause-effect analysis methodologies. For this type of faults, the existing regulations such as NTP 342 and NTP 509 were taken into account because these valves are safety ones [15], [16]. The root cause analysis was performed by means of fault tree analysis. Figure-8 shows a fragment of this, and Table-5 shows a fragment of the mode and effect analysis of the failure to calculate the priority risk number (PRN). The Eqn. (7) was used [7], [17]-[22].

$$PNR = S * O * D \tag{7}$$

Where, *S*: Degree of severity, *O*: Failure occurrence factor, *D*: Detect ability factor.

Table-5. Analysis of the mode and effect of design failure.

<table>
<tr><th colspan="11">FMECA IN A THERMO-ELECTRIC</th></tr>
<tr><th colspan="4">SYSTEM: 07 BOILER</th><th colspan="2">INSTRUMENT: PSV-1T SAFETY VALVE</th><th colspan="5">ANALYSIS GROUP: Process engineers, mechanical maintenance and regulation and control.</th></tr>
<tr><th colspan="4">SUBSYSTEM: 07PP0DK</th><th colspan="2">REFERENCE: P&ID 4400-01-03-0001</th><th>N°1</th><th colspan="3">Date: 19-08-2017</th><th>Sheet N°: 1</th></tr>
<tr><td colspan="2" rowspan="2">FUNCTION</td><td colspan="2" rowspan="2">FAILURE MODE</td><td colspan="2" rowspan="2">CAUSE</td><td rowspan="2">FAILURE EFFECT</td><td colspan="4">INDEX</td></tr>
<tr><td>S</td><td>O</td><td>D</td><td>PRN</td></tr>
<tr><td rowspan="5">1</td><td rowspan="5">Staying Airtight During Normal Work Operation</td><td rowspan="3">A</td><td rowspan="3">Pass</td><td>1</td><td>Decalibrated</td><td rowspan="3">It does not directly affect production. but, it produces losses of steam, which are reflected in the increase of the water of reposition, increasing the consumption of demineralized water.</td><td>2</td><td>4</td><td>2</td><td>16</td></tr>
<tr><td>2</td><td>Wear (Seat-Plug)</td><td>2</td><td>4</td><td>2</td><td>16</td></tr>
<tr><td>3</td><td>Deformation (Seat-Plug)</td><td>2</td><td>4</td><td>2</td><td>16</td></tr>
<tr><td rowspan="2">B</td><td rowspan="2">Leaks</td><td>4</td><td>Steam Through the Body</td><td rowspan="2">It can affect the production, it produces steam losses, it also generates an unsafe situation for the operator.</td><td>3</td><td>1</td><td>4</td><td>12</td></tr>
<tr><td>5</td><td>Steam by Welding</td><td>3</td><td>1</td><td>4</td><td>12</td></tr>
</table>

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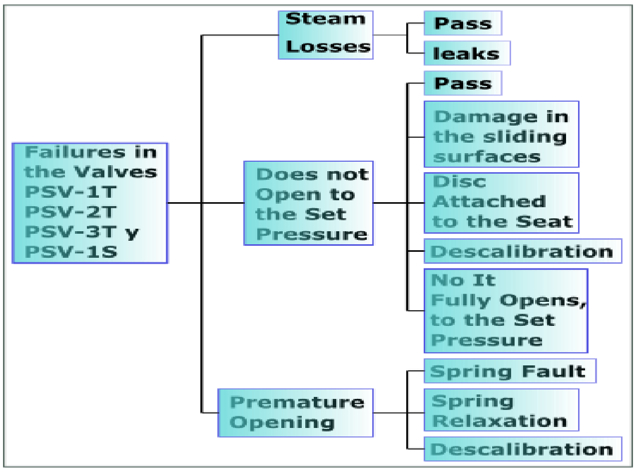

Figure-8. Fault tree analysis.

IMPLEMENTATION OF THE FUZZY SDDF

Once the most critical instruments were determined and the root cause of the most common failures in these instruments, it was decided to implement an SDDF. Due to the nature of the faults, it was determined that fuzzy logic was used in this. Figure-9 shows the *PI&D* diagram of the online condition monitoring system. This diagram was developed following the standards established in the ANSI/ISA-5.1 of 1984, Instrumentation Symbols and Identification, which establishes the symbols to be used to represent the instruments, as well as the codes that must be used to name each instrument.

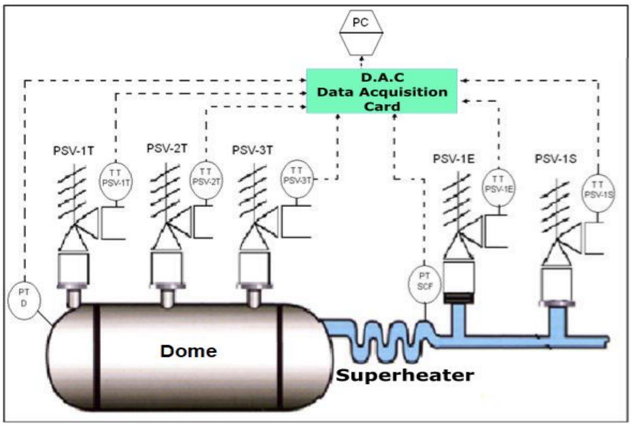

Figure-9. PI & D diagram of the online condition monitoring system.

Where:
TTPSV-1T = Temperature sensor located in the exhaust pipe of the PSV-1T valve.
TTPSV-2T = Temperature sensor located in the exhaust pipe of the PSV-2T valve.
TTPSV-3T = Temperature sensor located in the exhaust pipe of the PSV-3T valve.
TTPSV-1S = Temperature sensor located in the exhaust pipe of the PSV-1S valve.
TTPSV-1E = Temperature sensor located in the exhaust pipe of the PSV-1E valve.
PTD = Pressure sensor located in the dome.
PTSCF = Pressure sensor located in the final superheater.

Fuzzy Modeling

The main advantage of a fuzzy system is that precise knowledge and the development of complex mathematical models are not necessary. The system used will be Takagi-Sugeno (TS). This was taken for its simplicity that generates a more efficient system in computer terms than a Mamdani system. Another interesting feature is that it combines a mathematical description and a linguistic description in a single model which allows it to adapt better to mathematical analysis, it is also easily combined with optimization and adaptive techniques. Finally, fuzzy TS models with consequent constants (zero order) that can be easily handled as long as the fuzzy sets assigned to the linguistic input variables strictly use triangular partitions [3], [23]-[26].

Let then be the Takagi-Sugeno fuzzy zero-order model (sometimes called the Wang-Mendell model) that represents the system whose rule base consists of rules with consequent constants expressed as shown in the Eqn. (8) [4], [27], [28]:

$$fy(t)isA_1^{i1}yy(t-1)isA_2^{i2}y\ldots yy(t-n+1)isA_n^{in}yx(t)isB_1^{j1}y\ldots yx(t-m+1)isB_m^{im}theny_i(t+1)=\emptyset^{i1,\ldots in,j1\ldots jm} \quad (8)$$

Where A_p^{ip} y B_q^{jq} are linguistic terms associated respectively with the variables $y(t-p+1)$ y $x(t-q+1)$ and $\emptyset^{i1,\ldots in,j1\ldots jm}$ is a real constant. When a strict partition of the different universes of input speech with triangular membership functions is assumed, at each sampling time τ any input variable can be described at most

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Table-6. SDDF FAM of the PSV-1T Valve.

		PRESSURE							
TEMPERATURE		**N**	**HN**	**HL**	**HLM**	**HM**	**H**	**VH**	**EH**
	N	**FNN**	**FNN**	**DNOFP**	**DNOFP**	**DNOFP**	**DNOFP**	**DNOFP**	**DNOFP**
	HN	FNN "OR" PP	FNN "OR" PP	DNOFP "OR" PP	DNOFP "OR" PP	DNOFP "OR" PP	DNOFP "OR" PP	DNOFP "OR" PP	DNOFP "OR" PP
	HL	PP	PP	DNOFP "OR" PP	DNOFP "OR" PP	DNOFP "OR" PP	DNOFP "OR" PP	DNOFP "OR" PP	DNOFP "OR" PP
	HLM	PP "OR" PO	PP "OR" PO	DNOFP "OR" PP	DNOFP "OR" PP	DNOFP "OR" PP	DNOFP "OR" PP	DNOFP "OR" PP	DNOFP "OR" PP
	HM	PO	PO	FNA "OR" AP	FNA "OR" AP	DNOFP	DNOFP	DNOFP	DNOFP
	H	PO	PO	FNA "OR" AP	FNA "OR" AP	DNOFP	DNOFP	DNOFP	DNOFP
	VH	PO	PO	FNA "OR" AP	FNA "OR" AP	DNOFP	DNOFP	DNOFP	DNOFP
	EH	PO	PO	FNA "OR" AP	FNA "OR" AP	DNOFP	DNOFP	DNOFP	DNOFP

by two linguistic terms, so in the case of having a system of n + m entries, at most 2n + m rules, would be activated for any input vector. This property provides good computational efficiency and offers advantages over other approaches such as neuro-fuzzy systems.

The Takagi-Sugeno system used will have a very simple structure of operations "min-max" given by the Eqn. (9):

$$\mu_{A\to B}(x,y) = max\,\{min[\mu_A(x), \mu_B(y)]\,, 1-\mu_A(x)\} \quad (9)$$

Finally, when we try to obtain a solution to a decision problem, what we want to obtain as output is a number and not a fuzzy set. Therefore, given the outputs of the individual consequents y, the total output and the diffuse Takagi-Sugeno model (defusification or concretion) is calculated using the Eqn. (10) [2]:

$$y = \frac{\sum_{i=1}^{r} w_i(x) * y_i}{\sum_{i=1}^{r} w_i(x)} \quad (10)$$

Taking into account the SDDF raised above and taking as an example the PSV-1T valve the inputs will be TP-DOMO: Pressure sensor in the dome, TT-PSV1T: Temperature sensor in the PSV-1T valve exhaust pipe and the output is PSV-1T: PSV-1T valve. Table-6 shows a fraction of the Takagi Sugeno diffuse model of zero order results:

The rule base consists of 64 rules, where each entry has 8 linguistic variables assigned. In the case of the TP-DOMO signal with the TT-PSV1T signal, the linguistic variables are: "N: Normal", "HN: High Normal", "HL: High Low", "HLM: High Low Medium", "HM: High Medium "," H: High "," VH: Very High "," EH: Extremely High ". On the other hand the linguistic variables assigned to the output are: "FNN: It Works Well When the Process Is in Normal State," FNN "OR" PP: It Works Well When the Process Is in Normal State or Presents Pass "," PP: Presents pass "," PP "OR" PO: Presents Pass or Premature Opening "," PO: Premature Opening "," DNOFP: Did not open to the firing pressure "," DNOFP "OR" PP: Did not open to the firing pressure or Presents Pass "," FNA "OR" AP: Works Well When the Process Is in abnormal State or Premature Opening "," FNA: It Works Well When the Process Is In Abnormal State ". The membership functions of each linguistic variable are triangular partitions and are shown in Figure-10 and Figure-11.

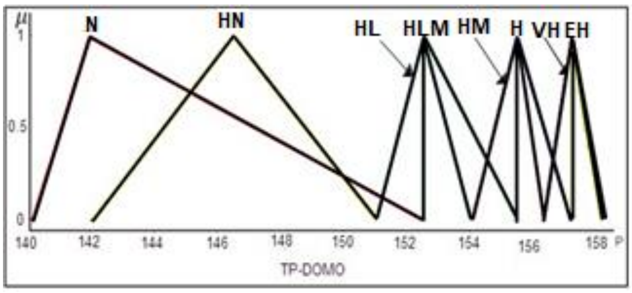

Figure-10. TP-DOMO membership function

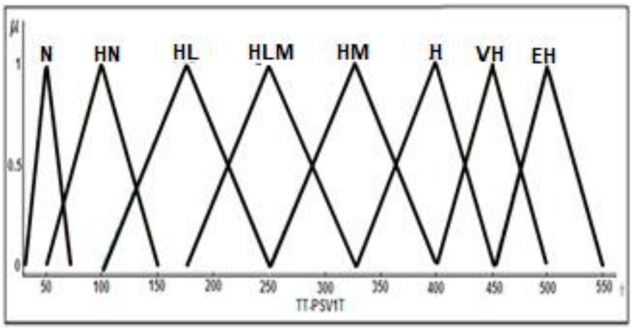

Figure-11. Membership function TT-PSV1T.

SYSTEM VALIDATION

Once the fault detection and diagnosis system have been programmed; we will proceed to validate it. The validation will be done through simulations. This was carried out using the tools provided by the MATLAB Simulink software and its Fuzzy Logic Toolbox.

Figure-12 shows the block diagram in Simulink of the fault detection and diagnosis system called FPSV1T. Here, the TP-DOMO input which will be common for the SDDF of the PSV-1T, PSV-2T and PSV-3T valves can be seen. Within this, there is a step named TP-DOMO to simulate the input coming from the pressure sensor in the dome. An oscilloscope named TP_DOMO was also placed to observe the value of the said signal. In the center, the SDDF for the PSV-1T valve is observed. Within this, we have the tool of Simulink Fuzzy Logic Controller with *Ruleviewer* named SDDF PSV-1T in which was imported from the Workspace of MATLAB the system of detection and diagnosis of faults of the PSV-1T valve programmed in the previous section. At the entrance, a step named TT-PSV1T was placed to simulate the input coming from the temperature sensor located in the PSV-1T valve's exhaust pipe. There is also an oscilloscope named TT_PSV1T to observe the value of the said signal. In the output, we have an oscilloscope named PSV-1T to observe the value of this.

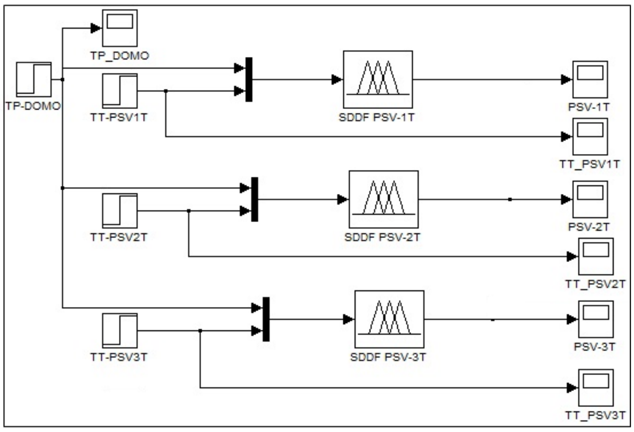

Figure-12. Block diagram in Simulink of the fault detection and diagnosis system.

For validation, the inputs will have the following values: TP-DOMO = 152, TP-SCFINAL = 138.5, TT-PSV1T = 270, TT-PSV2T = 125, TT-PSV3T = 350, TT-PSV1E = 50, TT-PSV1S = 90 Once simulated, you have to: With these seven input conditions, the outputs of the PSV-1T and PSV-2T valves take the values observed in Figures 13, 14.

Once simulated we have that these 7 conditions of entry generate the following diagnosis: PSV-1T = 7.07, PSV-2T = 2.4, PSV-3T = 5, PSV-1E = 7, PSV-1S = 7.54, which corresponds to valve PSV-1T does not open to trip pressure or presents pass, PSV-2T valve works well when the process is in normal state or presents pass, PSV-3T valve opening premature, PSV-1E valve does not open to the firing pressure or present pass and valve PSV-1S Works Well When the Process Is In Abnormal State. For the validation, the SDDF was simulated by taking multiple random values for each one of the entries and the answers given by the SDDF were submitted to the analysis of the experts in the process, who corroborated that the answers were correct. Therefore, we can assure that the model is valid since it solves the problems posed and behaves as the experts expected, which will finally be the users.

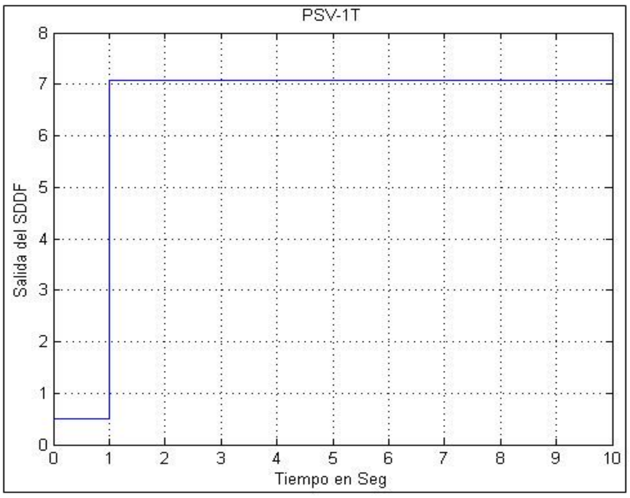

Figure-13. PSV-1T Valve SDDF Output.

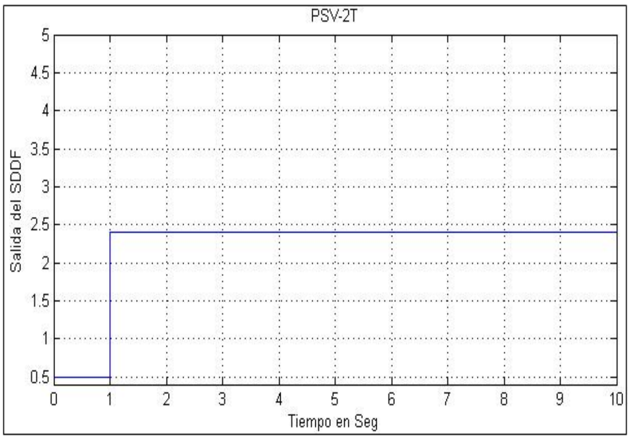

Figure-14. PSD-2T valve SDDF output.

RESULTS AND DISCUSSION

The documentation and definition of the specifications of each one of the studied systems allow determining the operating characteristics of each of them, being the basis for the development of Failure Mode and Effect Analysis, Root Cause Analysis and fuzzy SDDF.

The application of the mode analysis and failure effects allow the analysis of each of the possible causes of failure and thus determine for which failure modes an SDDF is necessary according to the level of impact that this generates to the process. Likewise, the SDDF must be focused on the detection and diagnosis of the root cause that causes equipment failure. Therefore, the identification of this constitutes the main key to determine which automatic methodology would be the most efficient at the time of implementing the SDDF.

In this paper, after having selected the most critical instruments of the steam generator of a Thermo-Electric, a diffuse detection and fault diagnosis system was implemented. With the validation of this system through simulations and taking random values of the entries, good preliminary results were obtained; the presented work shows that the fuzzy SDDF offers important advantages by allowing the incorporation of human reasoning as well as being a robust, efficient and simple method.

CONCLUSIONS

The problem of investment in the Colombian industry in systems of detection and diagnosis of faults (SDDF) is that the industry is composed of many systems and hundreds of instruments. The design of a single system to detect and isolate all defects prematurely may be impossible due to the amount of the initial investment. To remedy this problem, the hybridization of automatic methodologies with systematic methodologies is carried out. Through the use of systematic methodologies, selection methodologies such as the one proposed in this article can be developed in order to determine which instruments really require an SDDF. This methodology emphasizes those function failures that have an impact on safety, in the process and that violate the environment due to the high impact they generate.

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