Fuzzy Diagnostic Systems of Rotating Machineries, some ELETRONORTE's applications

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***Abstract*— This work reports the project of an expert predictive system used for on line diagnosis of problems in electric equipments used in energy generation and transmission power plants. Some times, the use of corrective maintenance increases the production costs and reduces the resource availability in electric power plants. Detailed observation of the behavior of complex equipments along the time allows fast and reliable identification of an anomaly. In some cases, the anomalous behavior lead to production discontinuities in the plant, a common situations when obsolete preventive maintenance methods are used. Using the tool described in this work, these situations are avoided and the maintenance costs are reduced. The diffusion of this type of paradigm in generation and transmission power plants allows a cheaper energy with more quality to the final consumer.**

***Index Terms*— Monitoring Systems of Electric Devices, Expert Diagnosis Systems, Transmission and Generation of Electric Energy, Fuzzy Logic.**

I. Introduction

The efficiency of the maintenance techniques applied in energy generation power plants is improved when expert diagnosis systems are used to analysis information provided by the continuous monitoring systems used in these installations. There are a large number of equipments available in the power plants of the North of Brazil Electric Company (ELETRONORTE). These equipments operate continuously because are indispensable for the correct functioning of the generation and transmission systems of the company. Anomalies in the operation of these devices can be detected with the use of intelligent diagnosis tools which analysis the information of the continuous monitoring systems and, based in a set of qualitative rules, indicate the best procedures to avoid the fail of the equipments

The best maintenance strategy used in each equipment of the company should consider factors as: equipments importance for the production process, acquisition cost and failure rate. To accomplish this task, one of the three maintenance techniques more used nowadays is chosen: corrective, preventive or predictive [1]. In the predictive maintenance, an operational report of the equipment's condition is emitted using the information collected by the continuous monitoring system. The formulation of such report is a task divided in the following stages: 1) Anomaly identification that can be occurring in the equipment; 2) Detection of the anomalous component; 3) Evaluation of the severity of the fault; and 4) Estimation of the remaining life time of the equipment. The predictive maintenance policies is an efficient practice to identify problems in hydrogenerators that will increase reliability, decrease maintenance costs, limit service failures and increase the life of the machines.

Recently, well successfully applications of predictive techniques have been reported. In [2] is presented an intelligent system for predictive maintenance addressed to the diagnosis in real-time of industrial processes. In [3] a fault detection and isolation scheme of sensor and actuator is presented. The project considers multivariate dynamic systems with uncertainties in the mathematical model of the process. Detailed studies on the robustness of anomalous systems of identification in presence of modeling errors is also reported in the survival paper [4].

Nowadays, the expert diagnosis technologies available in the market still are in maturation process. The tools commercially available have restrictions in the information exchange with the company's legacy systems. The users normally can't change the software structure and don't know the conceptual data base model. Due to these limitations, the company who uses this kind of paradigm is in a difficult situation when software modifications, not considered in the initial project, are necessary to adjust it to a specific application.

Currently, there are innumerable monitoring systems in the ELETRONORTE, one for each kind of equipment. These systems does not use the same data storage structure. Considering this characteristic, the software application proposed in this work must be flexible to allows the communication with the various data bases in the company. The modular architecture that is proposed for this application is suitable for this reality. New anomalies identification technologies can be incorporated in the diagnosis tool, facilitating its maintenance. Communication resources with OPC servers [7] results in a considerable reduction of costs related to the acquisition and installation of sensors, since many of the signals used in the diagnosis systems are already available in the supervisory systems of the installations of the company. The allocation of intellectual resources in the project and development of applications of this nature is an investment that can lead the ELETRONORTE a vanguard position front its direct competitors in the power electric market that use third part tools.

In this work is presented the project of a diagnosis system used, initially, in rotating machineries (synchronous generators and compensator). The work is organized as follows: in the sections II and III are presented the monitoring systems used in the synchronous generators and compensator, named, SIMME and VIBROCOMP, respectively; in the section IV are presented the methodologies used in the project of a diagnosis system for synchronous compensator; in the section V are presented the main paper conclusions and some perspectives.

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II. Hydrogenarator Monitoring and Diagnosis System - HMDS

This tool is used in the decision process of the predictive maintenance policies of the company related to hydroelectric plants (HEP). Currently, the HMDS is in operation in the following installations: in the Tucuruí HEP in the Pará state, where 12 hydrogenarators are monitored; in the Coaracy Nunes HEP, in the Amapá state, where 3 hydraulic units are monitored; in the HEP Samuel, in Rondonia state, with 5 generation units monitored; and in the HEP Balbina, in Amazonas state, with 1 generation unit monitored

There are two main components in the HMDS: the monitoring module, named Sistema de Monitoramento de Máquinas Eletromecânicas - SIMME; and the analysis and diagnosis expert module. The main SIMME characteristics are the following:

- **Flexibility in the configuration** - the analyst can configure all the input signals defining the acquisition rate, calibration parameters, alarm limits and filters configuration;
- **Data storage capabilities** - when the alarm limits are violated, the monitored signals are stored in the data base (SQL Server) for the posterior analysis of the occurrences. The records also can be realized in programmed form for the users and periodically to create the trend curves.
- **Communication with OPC Server** - some signals can directly be read from the supervision system of the HEP, avoiding the installation of new sensors;
- **Real time signal analysis** - the operators can monitor, in real time, the behavior of the equipments in order to detect imperfections in the components of the hydraulic units. This analysis can be made in time and frequency domains;
- **Events notification** - when events are detected, the signals are stored in the data base, and e-mails are sent for the users that can receive this type of notification;

The Table I present some signals monitored by SIMME in the HEP Tucuruí.

TABLE I
SIGNALS MONITORED BY SIMME IN HEP TUCURUÍÍ

Tag	Description	Unit	Nature
MGG	Generator's Guides Vibr.	μm	Vibration
MGT	Turbine's Guides Vibr.	μm	Vibration
PCE	Spiral box´' Press.	bar	Pressure
PT	Turbine cover's Press.	bar	Pressure
PS	Suction pipe Press.	bar	Pressure
OT	Oil's Temperature	$^{\circ}$C	Temperature
IT	Iron's Temperature	$^{\circ}$C	Temperature
P	Active Power	MW	Power

In the diagnosis and analysis module the maintenance engineering of the company analysis the operational condition evolution of the hydraulic units. This module presents the following characteristics:

- **Fault detention** - a logic fuzzy inference unit is used to identify the abnormal operation modes. The knowledge base of this unit can be edited by the analyst to determine cause and effect relations and emulate the hydraulic units behavior in these situations;
- **Operational condition prognostic** - Predictive's models are used to represents the normal operational condition of the units. Comparing the real unit behavior and the output of the models, slow dynamic changes in the equipment are identified and the time until the fault is estimated.
- **Report Generation** - Graphical tools are available to analysis the signals in the time and frequency domains to detect inter correlations between the monitored signals and elaborate the operational reports;

In the Figs. 1 and 2 are presented the interfaces of the SIMME and the diagnosis module of the HMDS, respectively.

Fig. 1. Main Interface of SIMME, the monitoring module of the HMDS.

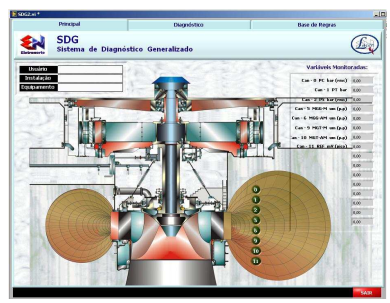

Fig. 2. Main Interface of the diagnosis module of the HMDS.

III. Synchronous Compensator Monitoring and Diagnosis System - SCMDS

This tool address the maintenance engineering of the synchronous compensator (SC). Currently, it is in operation in: Vla do Conde substation, Pará state, where two SC are monitored; and Marabá substation, Pará state, where one SC is monitored. In the Fig. 3 the CPAV01, one of the SC monitored in the Vila do Conde substation is presented.

The software structure of the SCMDS is also divided in two components:

1) **Monitoring module** - Called VIBROCOMP, witch collects, manipulate and present signal of vibration, temperature and pressure in the SC.
2) **Diagnosis Module** - it access the monitoring registers and uses an inference engine to identify and analysis the faults;

The Figs. 4 and 5 present the VIBROCOMP and expert diagnosis module main interfaces, respectively.

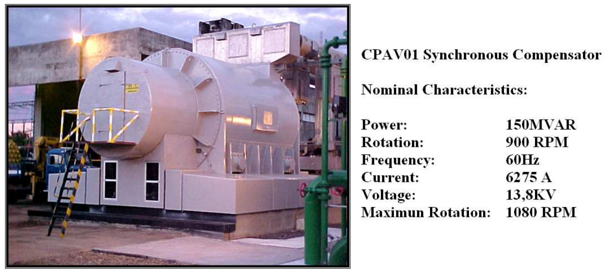

Fig. 3. CPAV01, synchronous compensator of Vila do Conde substation-PA.

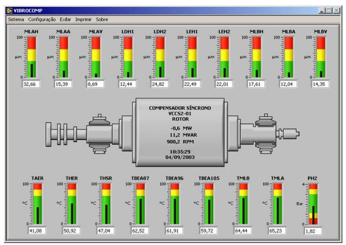

Fig. 4. Main interface of VIBROCOMP, the monitoring module of the SCMDS.

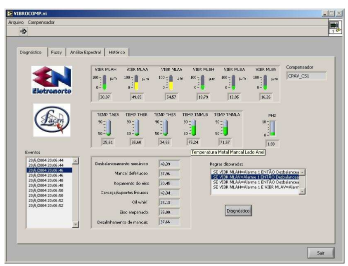

Fig. 5. Main interface of the diagnosis module of the SCMDS.

In the Table II are presented some of the signals monitored by the VIBROCOMP that will be used in this work to evaluate the behavior of the CPAV01.

TABLE II
SIGNALS MONITORED IN VIBROCOMP

TAG	Description	Unit	Nature
MLAH	Guide Ring Horiz. Vibr.	μm	Vibration
MLAA	Guide Ring Axial Vibr.	μm	Vibration
MLAV	Guide Ring Vert. Vibr.	μm	Vibration
MLBH	Guide Bomb Horiz. Vibr.	μm	Vibration
MLBA	Guide Bomb Axial Vibr.	μm	Vibration
MLBV	Guide Bomb Vert. Vibr.	μm	Vibration
LDH1	Right Side Horiz. Guide Vibr.	μm	Vibration
PH2	Hydrogen press.	bar	Pressure
ROT	Rotation	RPM	Speed
P-SUM	Active Trifasic Power	MW	Power
Q-SUM	Reactive Trifasic Power	MVAR	Power
TBEA87	87 Stator Bars Temp.	C^o	Temperature
TAER	Input Water Temp.	C^o	Temperature

IV. EXPERIMENTAL RESULTS

A. Synchronous Compensator Predictive Models

In this section a case study will be presented where the structure of a parametric model was identified to emulate the normal behavior of a SC. The information used in the model estimation was stored between 03/01/2008 and 25/03/2008 with the VIBROCOMP monitoring system. The monitored equipment was the CPAV01, located in the Villa do Conde substation. In this period the SC operate in its normal condition. The estimation of a mathematical model to describe this electric equipment is a practical procedure described as follows:

1) Statistics Analysis to identify dynamic relations between the monitored variables;
2) Choice of the model structure;
3) Model validation and estimation;

In the first stage was used the following auto-correlation function (ACF) to identify the time relations of a discrete time signal $y(t)$:

$$r_\tau = \frac{\sum_{t=\tau+1}^{N} [y(t)-\bar{y}]\,[y(t-\tau)-\bar{y}]}{\sum_{t=1}^{N} [y(t)-\bar{y}]^2} \qquad (1)$$

where $\bar{y}$ is the average value of the signal $y(t)$ and t is the discrete time, an integer multiple of the sampling interval.

The ACF analysis indicate that some monitored signals ($P-SUM$ and ROT) show characteristics approximately random and behaves like uncorrelated white noises. Other signals ($TAER$, $PH2$, $MLAH$, $Q-SUM$, $TBEA87$ and $LDH1$) are correlated to previous values and can be described as Autoregressive Moving Average Models (ARM) [5]. The ACF profile of these signals shows fixed partern in the first time delays and then a combination of damped exponential and sinusoids.

To evaluate the correlation between two discrete time signals $u(t)$ and $y(t)$ the following Crossed Correlation Function (CCF) was used:

$$r_{yu} = \frac{\sum_{t=\tau+1}^{N} [y(t)-\bar{y}]\,[u(t-\tau)-\bar{u}]}{\sum_{t=1}^{N} [y(t)-\bar{y}]^2} \qquad (2)$$

where $\bar{u}$ is the average value of the signal $u(t)$.

The profile and the amplitude magnitudes of the CCF analysis indicate that some monitored signals are correlated. The final result of the analysis is presented in the Table III. The interpretation of this table is the following: the signals of the left column are related to the signals of the central column in the delays specified in the right column. For example: the signal $TAER(t)$ is auto-correlated, and also depends on the signals $TBEA87(t)$, $TBEA87(t-1)$, $PH2(t-1)$, $PH2(t-2)$, $PH2(t-3)$ and successively. The intensity of the relationship between the signals is proportional to the order of presentation in the central column.

TABLE III
CROSS-CORRELATION OF THE VIBROCOMP SIGNALS

TAG	TAG Correlations	Delays
MLAH	LDH1	[5 7]
LDH1	MLAH, TBEA87	[5 7], [1 3]
PH2	Q SUM e TAER	[1 3], [1 3]
Q-SUM	PH2 TBEA87	[1 3], [1 2]
TBEA87	Q-SUM, LDH1 e TAER	[1 2], [2], [1 2]
TAER	TAER , TBEA87, PH2 , Q-SUM	[1 4], [0 1], [1 3], [0 2]

The choice of the best model structure was based on the information of the Table III. The statistical characteristics of the signals indicates that an Autoregressive Moving Average with External Inputs (ARMAX) model is a suitable topology to explain the dynamic relations of the monitored signals in this application. For the signal $TAER(t)$, for example, the following model structure is used:

$$TAER(t) = \sum_{i=1}^{4} a_i TAER(t-i) + \sum_{i=0}^{1} b_i TBEA87(t-i) + \epsilon(t) + c_1\epsilon(t-1) \qquad (3)$$

where ϵ is an uncorrelated white noise that, supposedly, corrupts the data, since the model is concerned in a stochastic environment. The signal $TBEA87(t)$ was chosen as the input of this model because of the relationship presented in the Table III. This signal presents big values for the CCF with the signal $TAER(t)$. Under an intuitive point of view, it is coherent to assume that the water refrigeration temperature depends of the stator bars temperature.

The model parameters estimation was realized in the Matlab environment using the System Identification Toolbox [6]. The estimation method used was the well known non-recursive least-squares [5]. In the Fig. 6 the results of the time domain model validation are presented. The sampling interval used is 1 hour, the same time used in the trend curves of the VIBROCOMP. The Fig. shows that the model can explain very well the dynamics of the signal in the analyzed time interval.

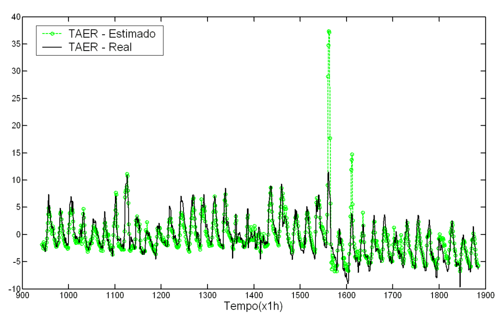

Fig. 6. Model validation of the signal $TAER(t)$.

A similar model estimation procedure was used for all the other signals monitored for the VIBROCOMP that presented relevant information of the SC. The set of models identified allows a mathematical representation of the CPAV01 normal behavior. Comparing models outputs with the real time signals it is possible to detect the occurrence of anomalous in this equipment.

B. Example of Expert Diagnosis System Project

In this section the project of an expert diagnosis system to detect faults in a SC will be described. In this paper a fuzzy inference system will be used to address this task [8]. This system maps the space defined by some of the signals monitored by the VIBROCOMP into a set of probability of faults in the SC. The project methodology used is delineated as follows:

1) **Chose the input variables** - this choice is based in the amount and quality of the information given by the monitoring system. The knowledge of the cause and effect relations involved in the equipment operation helps in this choice. A detailed study of the signal correlations is used to eliminate redundancies information, simplifying the inference unit structure;
2) **Choice of the output variables** - In this stage the following question should be answered: which faults should be detected?;
3) **Choice of the fuzzy sets** - For each input and output variables the acceptable and not acceptable levels must be determined. Moreover the precision related to the number of fuzzy sets and the level of overlapping must be specified.
4) **Rules definition** - Standard IF-THEN fuzzy rules are used to define the fault and normal behavior operation modes;
5) **Choice of the fuzzy operators** - this choice is based on aspects as computational effort and continuity;
6) **Validation of the Rule Base** - Simulation with artificial data is used to detect inconsistencies in the rule base;

In the first stage two strategies are proposed: a conventional one which considers only the instantaneous values registered in the VIBROCOMP as the input signals and another one which considers spectral information as wave forms and frequency content as input signals. In the current development stage of the SCMDS, the conventional strategy was chosen as the most suitable for one simplicity reason: the data storage structure of the SCMDS diagnosis module not yet contemplates spectral information of the monitored signals. The input signals to be used are the following ones: $MLAH$, $MLAV$, $MLAA$, $MLBA$, $MLBH$ and $MLBV$. The description of these acronyms can be found in the Table II.

The output variables are the faults that must be detected. For each fault the company maintenance engineering defined standards probability values. In the Table IV are presented the diagnosis system outputs and the probabilities values.

TABLE IV
SCMDS DIAGNOSIS MODULE OUTPUTS

Faults		Output Fuzzy Sets
F1	Mechanic Unbalance	10%, 20%, 70%, 90%
F2	Bearing Malfunction	30%, 40%, 70%
F3	Stationary/rotating parts contact	20%, 30%, 50%, 70%
F4	Housings/supports oscillation	10%, 20%, 70%, 90%
F4	Oil Whirl	10%, 20%, 70%, 90%
F5	Shaft Bent	10%, 30%, 40%, 60%
F6	Bearing Unbalance	10%, 20%, 30%, 70%

The fuzzy structure defined for each output signal is the following: for each fault a finite set of fault probability is supplied. These sets where based on the maintenance specialists experience. The validation tests of the inference system show betters results when the number of fuzzy sets describing each fuzzy variable is equal to the number of possibilities supplied for the specialists. Under a practical point of view, this project choice is based in the following argument: if a finite number of fuzzy outputs for each fault is defined, then the diagnosis system does not present results not expected in the project.

This project choice, however, does not guarantee the precision in the diagnosis. One another important aspect of the project is the fuzzy sets distribution along the universe of discourse of the output variables. Experimental results show that this distribution has great influence on the diagnosis system behaviour. Divergences between the expected value of the diagnosis system and the real values had been observed when the fuzzy sets were distributed uniformly along the variables range. This project choice, which is a common practice in most of the applications described in the literature [8], did not present satisfactory results for all type of defuzzification used in the application described here. The solution of these inconsistences is to specify not overlapping fuzzy sets, a little narrow located around the values of precisions defined for the specialists. Triangular functions with base size not greater than 10% shown greaty results. In the Fig. 7 is presented an example of sets distribution of the variable $F6$.

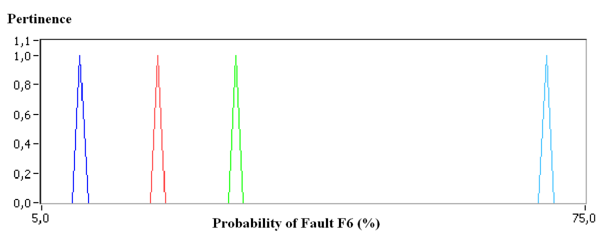

Fig. 7. Fuzzy sets of the output F6: Bearing Unbalance.

Fifteen rules had been supplied by the mechanics specialists, so that the diagnosis system can detect the anomalies described in the table IV. These rules use only vibration and temperature input variables. In the following, one of the specified rules is presented:

Regra 1: IF MLAH is Alarm 1 and MLBH is Alarm 1 THEN $F1$ is 70 and $F2$ is 30 and $F3$ is 50 and $F4$ is 20 and $F5$ is 70 and $F6$ is 30 and $F7$ is 20.

In this and all the other rules supplied for the specialists another peculiar characteristic can be observed: the antecedents are short and the consequents are long fault probabilities combinations. In the table V are presented the characteristics of the input variables pertinence functions.

TABLE V
FUZZY SETS OF THE VIBRATION INPUTS: MLAH, MLAV, MLAA, MLBH, MLBV AND MLBA.

Universe [0 100]	Function	
Fuzzy	Type	Interval
Normal	Trapezoidal	[0 0 30 40]
Alarm - 1	Triangular	[39.78 45 50]
Alarm - 2	Trapezoidal	[49.78 60 100 100]

After the modifications in the fuzzy sets distribution of the output variables and the choice of a precision set for the fault probability the diagnosis module present a satisfactory behavior. However, In the validation tests some divergences in the results related to the defuzzification method used had been observed. This is a project choice and the specialist should identify the most suitable operator for each application.

In relation to the others fuzzy inference operators, no significant divergences where observed. In its current development stage, the diagnosis module allows the use of the following methods: T-Norm operator min; Mandani's implication and maximum aggregation method.

V. CONCLUSION

In this work an estimation methodology of predictive models of a synchronous compensator (SC) was presented. The data used in the model estimation was stored in the VIBROCOMP monitoring system during normal behavior operation of the CPAV01, one of the SC monitored in the ELETRONORTE. The discrete linear models, structurally simple, explain very well the dynamic characteristics of the studied equipment. Using these models it is possible to detect, prematurely, problems in these equipments comparing the real system output with the model output. After detect the anomalies, the inference IF-THEN rules are used to identify the fault and present the corrective actions necessary to prevent the occurrence of a fault.

An excellent feature of the tool presented here is that new input and outputs can be added to the diagnosis module and each user has freedom to define his own rule base suitable for each type of equipment in the company. Until the present moment the tool is used in the diagnosis of SC and hydrogenerators. The reactor and power transformers monitoring and diagnosis is already studied as one future application of the diagnosis module.

Although the spectral approach is a solution very close to the real analysis that precedes the diagnosis of a fault, this methodology was not yet used because the data storage structure of the SCMDS not yet contemplates the frequency and wave form information of the monitored signals. The alterations are in progress and as soon as new results will be reported.

[1] Nepomuceno, L. X.; *Técnicas de Manutenção Preditiva*; Editora Edgard Blücher Ltda; Volume 2; 1989

[2] Mari Cruz Garcia, Miguel A. Sanz Bobi and Javier del Pico *SIMAP - Intelligent System for Predictive Maintenance Application to the health condition monitoring of a windturbine gearbox*, Elsevier, Computers in Industry, vol 57, 2006, 552568;

[3] Zhengang Han, Weihua Li and Sirish L. Shah; *Fault detection and isolation in the presence of process uncertainties*; Elsevier, Control Engineering Practice 13, 2005, pag 587-599;

[4] Paul M. Frank; *Fault Diagnosis in Dynamic Systems Using Analytical and Knowledge-based Redundancy A Survey and Some New Results*; Automatica, Vol. 26, No. 3, pp. 459-474, 1990;

[5] Lennart Ljung, *System Identification - Theory for the User*, PTR Prentice Hall, Englewood Cliffs, New Jersey, 1987;

[6] Lennart Ljung; *System Identification Tolbox 7 User's Guide*.

[7] Wolfgang Mahnke, Stefan-Helmut Leitner and Matthias Damm; *OPC Unified Architecture Textbook*, Springer, 1 edition, May 4, 2009;

[8] L. X. Wang; *A course in Fuzzy Systems and Control*,Prentice-Hall International, Inc.,1997,