New ways for terology through predictive maintenance in an environmental perspective

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Abstract: Terology is defined as the combined use of techniques of operational research, information systems and engineering, with the objective of accompanying the life cycle of facilities and equipments; it includes the definition of specifications referred to its purchase, installation and reception, as well as the management and control of its maintenance, modification and substitution and, still, its accompaniment in service. Under this perspective, maintenance is the core of terology and it correspond a subject that, instead of reducing importance of maintenance with the increasing of equipment reliability, it increases its role in the companies and obliges the increasing of the level of demand of professionals involved because of the new technical and environmental demands. This reveals the importance of this scientific area and the necessity to concentrate and to increase the research around it.

The maintenance area is an example that offers challenges to both science and companies in order to optimize the performance of equipment and facilities. But, the scientific developments, namely in this area, must be more and more environmentally friendly or, in other words, must close the technology to nature, guarantying its life through an adequate maintenance management.

It is because of this kind of challenge that the authors are developing new methodologies, almost antagonistic, because of the areas under development, namely diesel engines and wind generators, but as we will demonstrate, areas which are compatible and can contribute for a better environment.

In the case of wind generators, the methodology aims to optimize the cycles of production and, consequently, reduce the other kinds of energy production.

On the other hand, the methodologies for maintenance of diesel engines are based on environmental indicators that can predict the "health state" taking into account restrictions including health human factors among others.

The new methodologies will later be incorporated through new predictive maintenance modules in an integrated maintenance management system called SMIT (Terology Integrated Modular System).

The SMIT was developed as a traditional system, but it includes several innovations, like a fault diagnosis module, a non-periodic maintenance planning module and a generic on-condition maintenance module, among others. The new features will include, in the case of wind generators, on-line measures and the corresponding on-time treatment, using algorithms based on time-series forecasting and TCP/IP technology to transmit the signals. In the case of diesel engines, the algorithms are based on Markov chains and hidden Markov chains.

It is based on these developments and the new researches mentioned so far, that this paper is built upon, and we believe that it will be a contribution to the maintenance management area.

Key-Words: Terology; Maintenance management; Predictive maintenance; Diesel engines; Wind generators

1 Introduction

After many years since the appearance of first information systems for maintenance management, the basic maintenance problems remain, but with new boundaries.

The concept began from maintenance itself, continued throughout Terotechnology, Total Productive Maintenance (TPM), Terology, until Reliability Centered Maintenance (RCM).

Although techniques, methodologies and, in general, the research done in this scientific area has developed and provided a lot of knowledge, and because there has not been any scientific society in the specific field of maintenance, this has originated a dispersion of papers of this area within more general scientific areas.

This may be related to the weakness of industrial maintenance. This is usually the first industrial area where the manager reduces costs. In addition, due to the multiplicity of technical skills on the part of technicians, it becomes extremely difficult to find adequate human resource competences.

As a result of these last points or due to the enlargement of challenges made to maintenance, nowadays, new concepts and new background are developed around the Asset Management concept.

This puts maintenance as the core activity that integrates the global responsibility of all facilities, equipment and installations and, obviously, with the necessary skills to manage them.

It is based on this new background that the scientific community must do more research for new algorithms and develop new methodologies in order to anticipate the new challenges and the solutions to solve the new fragilities of the planet.

It is with an information system for maintenance, called SMIT [1], Terology Integrated Modular System, as a general base to manage the assets, as well as a strategic line of evolution of this system, that on-condition maintenance modules were introduced, and the corresponding research and development is being done around this theme.

The maintenance is one way to manage the life cycle of assets in order to increment its life with maximum reliability and, obviously, reduce the necessity of producing new products and equipments and, consequently, preserve the planet.

We are talking about a new economy, an ecologic economy, having as main objective the sustainability of the planet and, obviously, the maintenance will be or, in other words, is already a very important approach for that goal.

It is because of these reasons that this paper is developed supported by two strategic ways: the maintenance of diesel engines in an environmental perspective, and the maintenance of wind generators, having the system SMIT as a work-base.

The approach presented here for planned maintenance of diesel engines takes as reference environmental parameters instead of kilometers or operating hours, which is a new paradigm in maintenance area, added to the introduction of new algorithms for forecasting based on Markov chains [2] and, in particular, on hidden chains. In a regular Markov model, the state is directly visible to the observer and therefore, the state transition probabilities are easily determined. In a Hidden Markov Model, the state is not directly visible, but the variables that are influenced by the state are visible.

This new approach, instead of using traditional scheduling techniques, considers that each state does not correspond to an observable event, but is connected to a group of probability distributions of the state. Once the state is not directly visible, the state is an unknown variable; however, the variables that are influenced by the state are visible. The challenge is to determine the hidden variables from the observable variables. Each state has a probability distribution over the possible output tokens. Therefore, the sequence of tokens generated by a Hidden Markov Model (HMM) gives some information about the sequence of states.

Hidden Markov Models are especially known because of their applications in temporal pattern recognition such as predictive maintenance, speech, handwriting, gesture recognition, musical score following partial discharges and bioinformatics.

The evolution of degradation of engine conditions is done cutting the interval of conditions between the normal and the environmental limits, and considering several states within that interval. The Markov transitions have variable probabilities in each sub condition and the prediction of each new maintenance intervention is based on this technique as will be demonstrated later in this paper.

The maintenance of wind generators involves new problems, that begin with the traditional operational research methodologies, namely with the optimization of paths and resources but, also with the measurement of operating parameters that have the possibility to minimize faults and increment the optimization of planned maintenance. In this case, we use scheduling techniques and new hardware developed in order to receive and manage the measurement signals that would optimize the planning. The signal measurement, transmission, treatment and the algorithm inserted in SMIT, constitute a new approach in maintenance of wind generators.

These are the global approach that will be developed throughout this paper, beginning with SMIT and, then with these new on-condition approaches and their integration in the system, we will discuss new trends and new research areas and, finally, the conclusions of this paper.

2 SMIT – main modules

SMIT [1], [3], [4], [5], [6] is a Client/Server program, multi-database, allowing the installation of several clients and its configuration within the same platform. The program is accessed through the

Windows environment. SMIT allows the optimization of maintenance resources through the following tools:

- Characterization of maintenance objects;
- Suppliers (of equipments, parts and services);
- Human Resources Management;
- Tools Management;
- Stocks and Spare Parts Management;
- Fault Diagnosis;
- Work Orders;
- Planned Maintenance Management (including on-condition maintenance);
- Emission of Reports, Analyses and Improvement Plans.

SMIT always has the advantage to make the maintenance management easy because it includes the complexity of management in its structure but with a front-end that interacts with the user with the minimum complexity and minimum of operations and data. SMIT was developed using the scientific knowledge in this area and it is permanently up-to-date.

This approach was used because of the complexity, quantity of variables and diversity of situations that maintenance implies; they are reduced at a minimum with SMIT as explained below:

- To reduce preparation time and emission of Working Orders (WO);
- To print detailed WO with definition of resources and prediction of time for execution of the maintenance intervention;
- To establish priorities, taking in account the importance of equipment, the urgency of intervention and resources available (human and materials);
- To develop daily intervention plans, management of delays and work load, with the objective to minimize the response time, reply time and down time of the maintenance objects;
- To perform planned maintenance through the analysis of historic data and fault diagnosis;
- To perform detailed preventive inspection plans to fulfill all requirements for a good operation of maintenance objects;
- To manage spare parts, taking into account the adequate quantities adjusted in function of the level of equipment importance, the urgency of the intervention and the response of respective suppliers to supply the spare parts, in order to make possible its provision on time;
- To adjust the priorities of interventions, taking into account the evolution of parameters of duration and functioning among other variables, like reliability parameters;
- To compile the provisional costs for budget analysis, filtered by maintenance object, cost centre, location or others;
- To automatically calculate maintenance indicators allowing the emission of reports for periodic control by the responsible persons;
- To carry out the systematic accompaniment between the prevision and real needs for the resources: time, costs, people and suppliers;
- To perform the inventory management (equipment, parts, tools...) and financial calculation of depreciation of goods;
- To perform the management of spare parts, tools, …, and the indent orders to suppliers;
- To perform a dynamic planning of maintenance, updating automatically the maintenance object plan in function of the evolution of WO carried out;

One of the great advantages of SMIT is the minimum human resources required to work; the use of SMIT could be carried out by a person with basic knowledge of computer science in the user optics.

In the next figures, some significant SMIT screens are presented as examples.

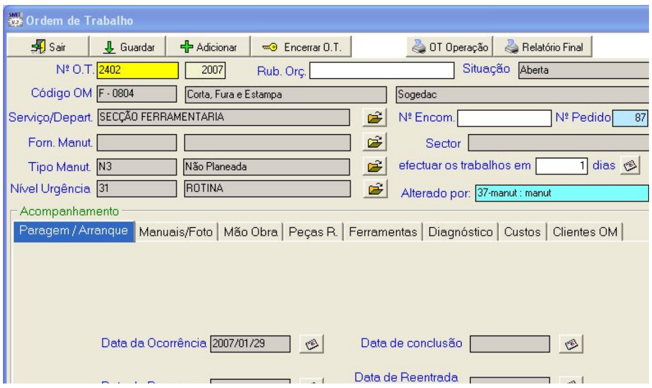

Fig. 1 – Launching a working order in SMIT program

The Planning and the working Orders are basic modules of a maintenance management program.

Fig. 2 represents a maintenance plan. Here, the user can choose the Maintenance Object (MO) in which he wants to implement a maintenance plan.

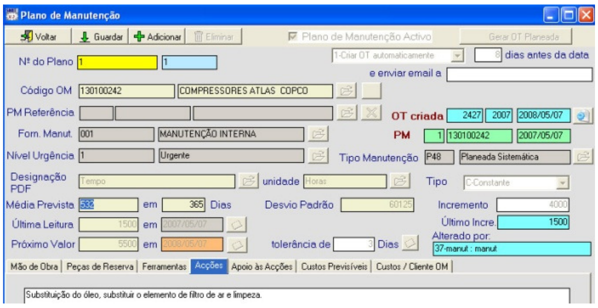

Fig. 2 – Maintenance Plan

The Gantt module allows the users to visualize plans in a graphical way, like WO required for interventions. With this interface, it is possible to modify the dates of any plan. The module has the advantage to offer a method of planning the work load of a maintenance department using "drag and drop" techniques.

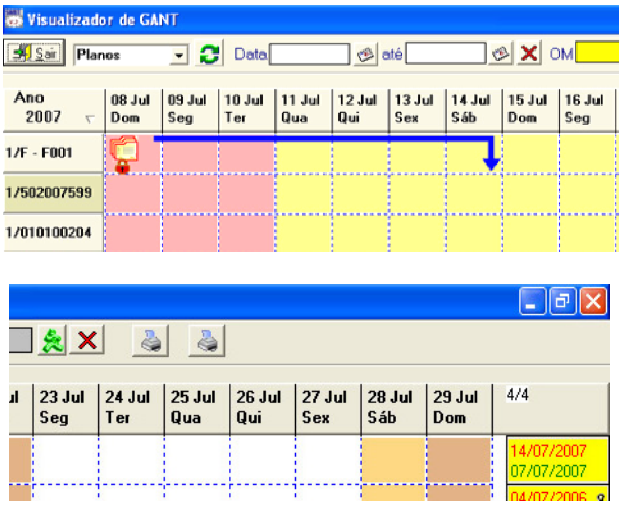

Fig. 3 – Two perspectives of Gantt Module

Another modules that are extremely important, because their capacity to aid maintenance, through a friendly interface, and the innovation that they introduced, are the fault diagnosis, both the base module of SMIT, with a three structure, fault-cause-solution, and the SADEX, a system based on a Fuzzy Case Based Reasoning (CBR) methodology [37].

Finally, this approach was extended since the maintenance management until the e-learning to the maintenance professionals, also using a CBR system [38].

In fact, the maintenance management with the approach that are being done by this way, has the potential to be transformed from a very complex activity with dense, disperse and complex information, to an activity that can be synergic to the top management, because it puts the technical, the logistic, the finance and related subjects, in dialogue with an integrated and comprehensive language; this is the terology approach.

3 Maintenance of Wind Generators

Wind turbines maintenance uses many techniques similar to the other maintenance objects. In this field many authors [7], [8], [9], [10] are working using acoustic techniques, vibration techniques, infrared images, stress measurement, zero crossing current analysis, artificial intelligence, only to name a few. Within this work, the main objective is to perform the fault detection through on-line data instrumentation, acoustic techniques, vibration techniques, infrared images, stress measurement, zero crossing current analysis, artificial intelligence, among others. Within this work, the main objective is to perform the fault detection through on-line data instrumentation.

3.1 The environmental problem

The techniques used for monitoring the wind systems condition are based in the following aspects:

- Vibration monitoring on generator and gearbox;
- Measuring the wind speed, using an analogue anemometer (inexpensive) and a ultrasonic anemometer WMT50 from Vaisala Company (for geographic signature of normal wind behavior);
- Active power measurement;
- Weather forecast using information from weather sites, tracking the wind velocity (using time series analysis);
- Classification using artificial intelligence;
- Time series analysis using regression techniques;
- Using a weather monitoring station (future development).

The hardware is based on commercial equipment from manufactures as National Company [12], also designed especially for SMIT software. In general, the signal condition follows the diagram shown in Fig 4.

The whole fault detection system is built around MATLAB Software routines for spectral analysis of current and vibration to extract essential information from the sampled time domain data, time series regression and artificial intelligent classification.

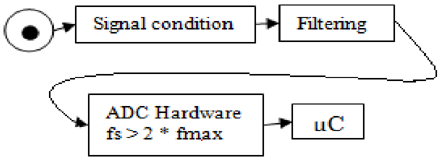

Fig. 4 – Generic electrical signal processing for data acquisition

3.2 New algorithms

1. The first algorithm uses an accelerometer to monitor vibrations on the gearbox and in the generator where the line currents are also monitored. To identify faults, two assays were performed. The first, an induction motor was used as motor and the second one as generator. In the first test, four induction motors were used, one healthy and three motors with some kind of damage provoked, like broken bars. The motors were tested with full load, half load and without any load (Fig. 5, up side). The same test was performed using now the motor as generator, and introducing loads (Fig. 5, down side). The acquisition was performed with a National Company USB 2.0 – Model 6251, the accelerometer Monitron MTN/1100CQ, a MTN/1100C and current sensors SEFRAM, model "SP 261". Fig 6, 7 and 8 show vibration signals.

Fig. 5 – Up: Example with motors. Down: the motor working as generator

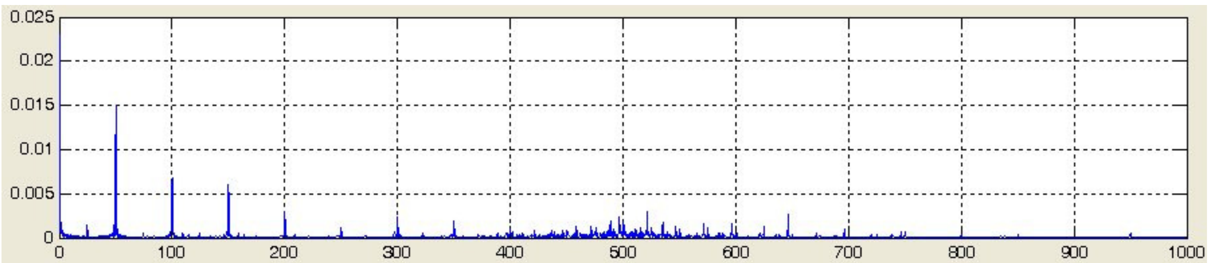

Fig. 6 – Vibration analysis using an FFT with 6000 points, fs= 2Khz. Healthy Motor, no load

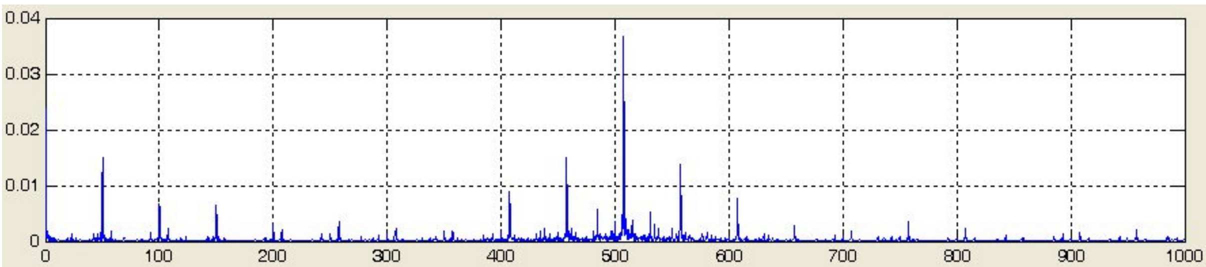

Fig. 7 – Healthy motor with full load

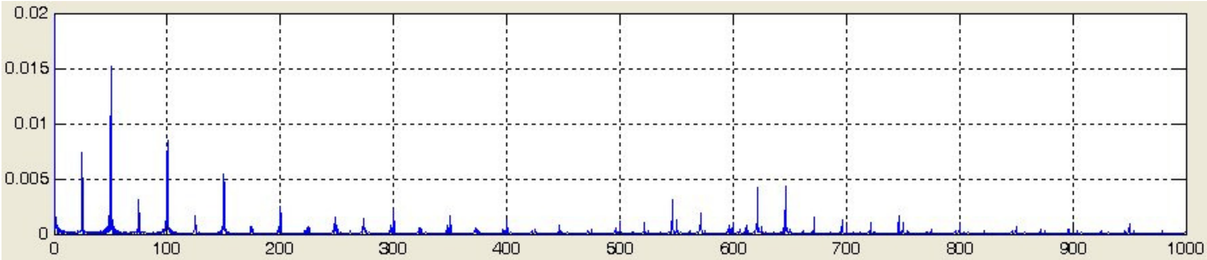

Fig. 8 – Motor with fault and with no load

2. The second step in this study was to monitor the wind speed. To accomplish this task a WMT50 from Vaisala [13] was used. This sensor uses ultrasonic technology to measure the wind speed and direction (Fig. 9, up side) and can be used for precise measurements, and for geographic signature of normal wind behavior. An RS232 interface communication permits to send and receive data. However, for a large scale implementation, the WMT50 is very expensive and in this case an analogue anemometer is recommended (costs about 50 Euro). The maintenance system only needs the wind speed. So, tests with an analogue cups anemometer were performed in this case. The number of revolutions per minute is registered electronically after some electronics.

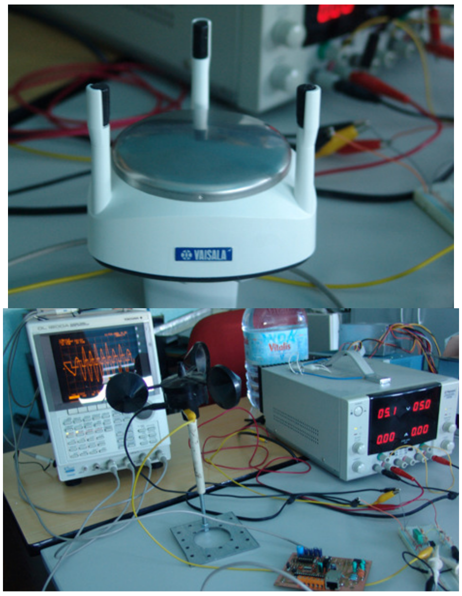

Fig. 9 –Up: WMT50 from Vaisala. Down: analogue cups anemometer

3. From wind and power measurement it is possible to predict the power curve. The main idea is to relate the power curve with normal or faulty condition.
4. Weather forecast is done based on web sites information, and by using the measurements given by the anemometer. The combination of this information is performed by using time series analysis.
5. Classification using artificial intelligence is performed basically using Support Vector Machines (SVM) only for deciding between a good situation and a fault situation [20].
6. Time series analysis using regression techniques are used to track some frequencies (see [11], [14] for more information) along time. This will give a time series to monitor and to check when they will tend to a situation where some fault will occur in the future. The regression is made based on SVR, ARMA and ARIMA models [21], [31].

These algorithms are all implemented in MATLAB Software where the simulations are performed and regression algorithms based on time series are compared.

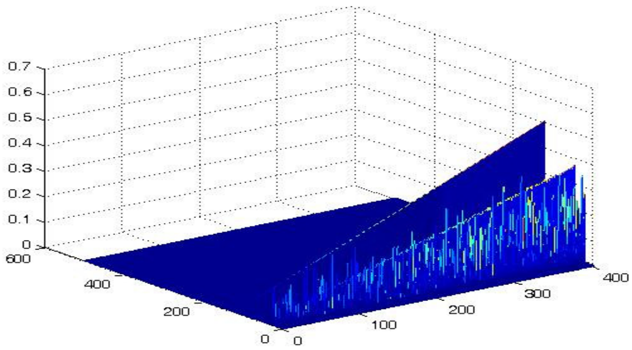

Fig. 10 – Simulated example as shown in Fig 11. FFT monitoring over time

3.3 New SMIT on-condition module

To integrate the methodologies described in section 3.2, a special hardware is necessary. Fig 12 shows the hardware.

The system can incorporate commercial acquisition hardware. For low cost implementations a special hardware is used based on CAN 2.0B network and Ethernet Network. The designed hardware uses microchip technology, PIC18F2685 for Can and ENC28J60 for Ethernet connectivity (Pic 18J86G60). In the instrumentation a special board incorporates a low pass filter and amplifier/attenuator electronics with cut-off and the gain set by software.

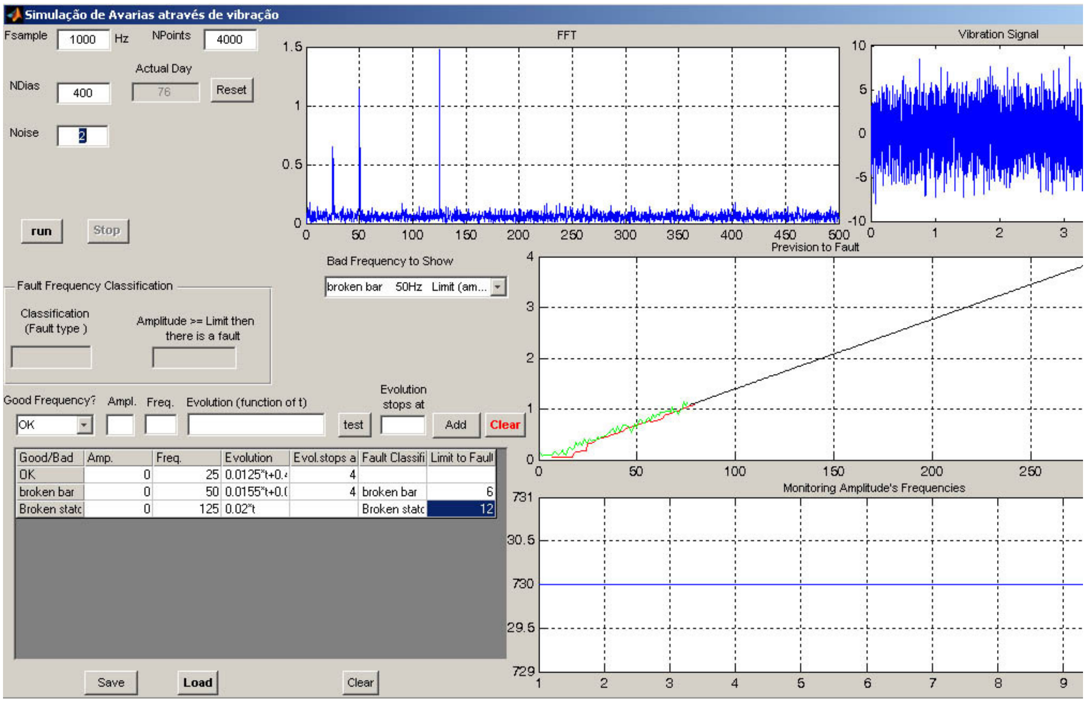

Fig. 11 – MATLAB program to monitor through time some key frequencies obtained from the vibration signal in the gearbox and generator

The SVM integration uses some measures in the corresponding vector (wind velocity, wind direction, low rotor velocity, high rotor velocity, active power and reactive power).

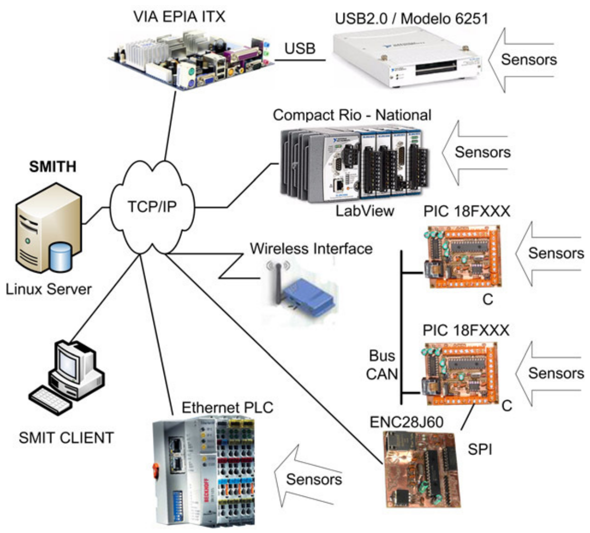

Fig. 12 – Maintenance Management System – SMIT and respective hardware for data acquisition

SVM can be seen in an easy way, as a mapping technique between measurement space and feature space (see Fig.13). More details can be seen in [20], [22], [23] and [24]. To perform the mapping kernel functions are used. The algorithm uses a training phase where measurements are classified. After training phase the algorithm can “tell” us the condition of new data.

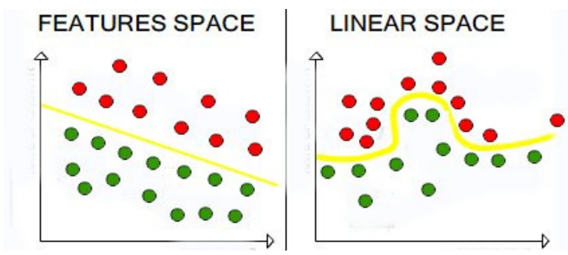

Fig. 13 –Transition between the Linear Space to Feature Space made through a kernel function

Figs. 14 show examples of real data measured in a wind turbine installed in Denmark [27]. It is also possible to simulate it in MATLAB Software - all the wind turbine behavior including wind statistical distribution. More details can be seen in [25], [26] and [27].

Using the SVM with the quadratic optimization algorithm, a performance classification around 93 % was achieved.

Using SVM with the least square optimization (called LS-SVM) method, a performance of 91% was achieved.

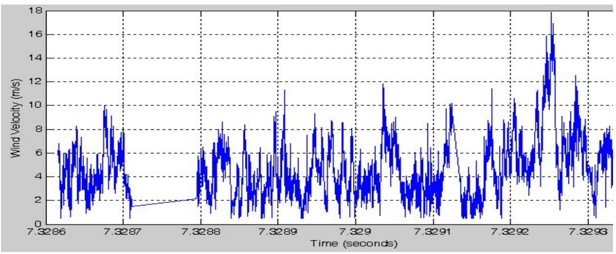

Fig. 14 – Wind velocity in the top located cup anemometer

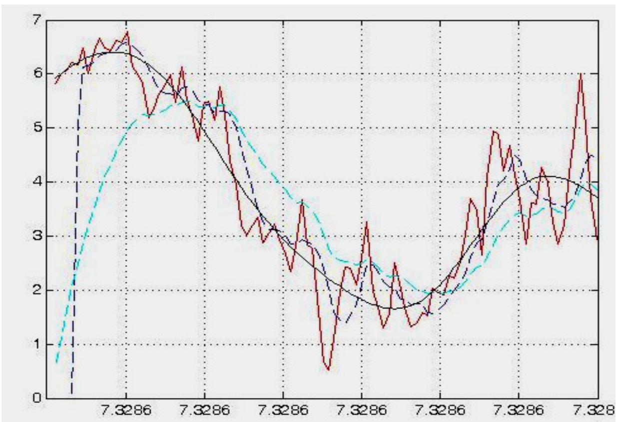

Fig. 15 – Example of time series forecasting (in this case, wind velocity). White, exponential smoothing, with alpha=0.4. Blue, moving average with N=5. Black color, SVR with RBF, 10.

4 Maintenance of diesel engines

4.1 The environmental problem

It is extremely important to ensure that all vehicles and, particularly the urban transport buses, operate safely and with reduced environmental impact. The more critical problems are associated with acceleration phases. Most information leads to the necessity to find the corresponding approach of state features and dysfunction feature recognition. The Hidden Markov Model (HMM) is very suitable to solve these kinds of problems.

The HMM is a statistical model, very suitable for modeling the dynamic time series. Under theory it can process randomly long sequences. The HMM is a dual random process, has hidden Markov chains with a given number of states and obvious random function of emissions. However, each function is relevant to the state of the chains and the hidden process is described by sequence of observations produced by the process. We define 12 stages or levels to classify the different dysfunctions. All other states are considered normal state.

4.2 A new paradigm of planning

Nowadays, predictive maintenance techniques have a very close analogy with medical diagnostic techniques. Whenever the human body has a problem, it exhibits a symptom. The nervous system and the look provide the information, which corresponds to the detection phase. Furthermore, if required, pathological testes are done to diagnose the problem. In sequence, suitable treatment is recommended.

By a similar way, dysfunctions or defects that occur in a vehicle or engine exhibit a symptom through the emissions or other indicators. However, this may or may not be easily detected with anticipation on vehicle detection systems, including human evaluation.

It is here that ecological predictive maintenance techniques emerge. These techniques detect symptoms of dysfunctions or defects that have occurred in vehicles or engines.

Predictive maintenance monitors mechanical condition, equipment efficiency and other indicators of state and attempts to forecast the approximate time for next failure. It is a methodology that permits to detect or to predict dysfunctions in engines and post-treatment equipment.

Within this last group it can be pointed out that Diesel Particulate Filters (DPF) are honeycomb or mesh devices placed within the exhaust stream that physically trap and oxidize Particulate Matter (PM). DPF must be paired with ultra-low sulphur fuels and use either passive or active regeneration systems to oxidize the PM in the filters. Passive filters require higher operating temperatures to work properly. Filters require some maintenance.

A comprehensive predictive maintenance program uses a combination of the most cost-effective tools to discover the present operating conditions of equipment and vehicles. Ecological predictive maintenance uses various techniques to evaluate the state, namely, gaseous effluents, particulates, noise level, and physical correlated measures, including temperature, oil and wear debris analyses.

Ecological variables can be used to determine the operating and mechanical condition of engines or vehicles. The major advantage is because these kinds of indicators can identify several problems before they appear and cause downtime. This can be achieved by conducting regular monitoring of engines or vehicles both on continuous basis and at scheduled maintenance.

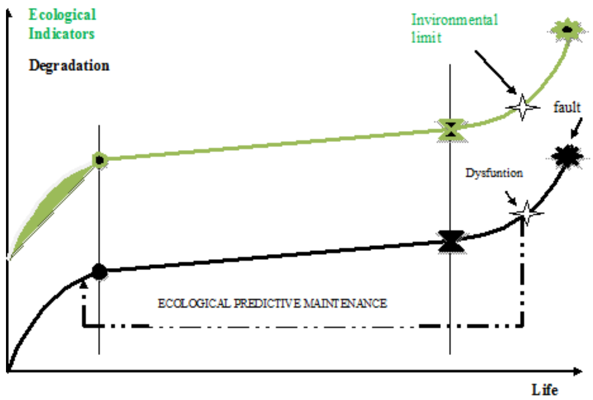

Fig.16 - How to predict the state

As we can see in fig. 16, environmental indicators monitoring, can detect wear parts, deteriorating or defective bearings, mechanical looseness and worn or broken gears. Noise measures can also detect misalignment and unbalance, before these conditions result in bearing or shaft deterioration. This is very important in replaceable equipment and parts, such as those associated to diesel engines and compressors.

The trending noise levels can identify poor maintenance practices, such as selection of improper bearings, housing clutches, or inadequate bearings installation and replacement. These can be a symptom of inaccurate shaft alignment or imprecise rotor balancing.

Measuring the amplitude of sound at certain frequencies can provide valuable information about the accuracy of shaft alignment and balance, about the condition of bearings or gears and the effect of associated vibration on the housings, piping and other structures.

Similarly with fault diagnosis, a certain rotating speed can be chosen to analyze the spectrum of noise that is compared with its corresponding normal operation mode to obtain the sates of engine or vehicles.

4.3 New algorithms

Real world processes, usually, produce signals or sequences of observations. The signals can be discrete or continuous. Examples of discrete signals are the characters of a finite alphabet written by an information system to recognize voice, and examples of continuous signals are temperature or pressure measures.

The signal generation can be stationary, where the statistical properties do not vary with time, or cannot be stationary. Furthermore, the signals can be of pure type or not pure, due to existence of noise or detection of other signal sources.

The objective is to characterize the real world signals through signal models. Data-driven methods directly use the data measured from the system [33].

Under the present research, the real world signals can be modeled through forecast models that explain the degradation of environmental variables and the respective condition of the systems or equipment.

The models that explain the behavior of signals (emissions) can provide the base for a theoretical description of how the states of vehicles, their technologies and the exploration conditions, influence the emissions, allowing decisions in order to guarantee an adequate output. On the other hand, the signal models allow the simulation of the source and, by this way, to predict how to avoid environmental impacts that violate the legal rules.

The signals can be modeled using deterministic or statistical techniques. The deterministic models exploit some specific properties from emission signals through forecasting values of signal variables (width, frequency). The statistical models try to characterize signal statistical properties, only (Gauss, Poisson, Markov, HMM, among others).

The HMM began to be developed at the end of the sixties, more precisely in 1966 [2]. The application of these models in recognition of words began to be used in the middle seventies [29].

During the last 15 years, the HMM models have been used in several fields, from the voice recognition, language modeling, recognition of written words, checking on-line of signatures, apprenticeship of human actions, fault detection in dynamic systems, to the recognition of “moving light displays” [28] [30].

The HMM models incorporate a double stochastic process, with a non visible stochastic process, because it is not seen (from which comes the designation of “hidden”), but can be observed through another stochastic process that produces the sequence of observations. The hidden processes consist of a group of states interrelated by probabilities of transition events. On the other hand, the observable processes, or not hidden, consist of a group of outputs or possible observations interrelated with the hidden states. For each possible state of the system, these outputs occur according to the probability density function (PDF).

Depending on the PDF, several types of HMM can be defined:

- Discrete – Discrete observations by type or converted into classes, according to a quantitative vector;
- Continuous – Continuous observations, with a probability density function usually translated by a normal distribution.
- Hybrid – Semi-continuous observations, divided between discrete and continuous.

4.3.1 Elements of a HMM

An HMM is an extension of Markov chains. This is a more complex problem than that described by Markov chains. In an HMM each state does not correspond to an observable event. Each sate is connected to a group of probability distributions of the states.

An HMM, for observations of discrete symbols, is characterized by:

- N – Number of states of the model. The finite group of individual possible states are identified by,
$$Q = \{q_1; q_2; q_3 \ldots q_N\};$$
- The state at instant t is specified by St; then, the sequence of states at instants t=1, t=2, t=3,…, t=T, is,
$$S = \{S_1; S_2; S_3 \ldots S_T\};$$
- M – Number associated to the classes of different observations by state. The individual symbols of different classes are specified by the group,
$$V = \{V_1; V_2; V_3 \ldots V_M\};$$
- The sequence of symbols or observations at instants, t=1, t=2, t=3,…, t=T, is,
$$O = \{O_1; O_2; O_3 \ldots O_T\}.$$

Consequently, the probability of observing such sequence of length T is given by:

$$P(O) = \sum_S P(O|S).P(S).$$

- The probability distribution of state transitions is represented by,
$$A = \{a_{ij}\}$$
Where,
$$a_{ij} = P[S_{t+1} = q_j | S_t = q_i],\ \ 1 \le i, j \le N.$$
- The probability distribution of symbols of observations $B = \{b_j(k)\}$ define the distribution of symbols or observation classes, in state j, with j=1,2,3,..., N, where $b_j(k) = P[O_t = V_k | S_t = q_j],\ \ 1 \le i \le M$.
- The distribution of initial state is $\pi = \{\pi_i\}$, or equivalent to $\pi = \{\pi_1, \pi_2, \pi_3, ..., \pi_N\}$, where $\pi_i = P[S_1 = q_i],\ \ 1 \le i \le N$.
- By convenience, the compact notation $\lambda = (N, M, A, B, \pi)$ is used or, yet, in a more reduced way, $\lambda = (A, B, \pi)$, to specify the complete group of model variables.

4.3.2 The three basic problems of an HMM

There exist three basic problems that must be solved so that an HMM can be used in real world applications:

- Problem 1: It is an evaluation problem. Given a sequence of observations, $O = \{O_1; O_2; O_3 \ldots O_T\}$ and the model $\lambda = (A, B, \pi)$, how can we calculate efficiently $P(O|\lambda)$ - the probability of sequence of observations - given the model?
- Problem 2: It consists of finding the best sequence of states. Given the sequence of observations $O = \{O_1; O_2; O_3 \ldots O_T\}$ and the model λ, how can the sequence of corresponding states $S = \{S_1; S_2; S_3 \ldots S_T\}$ be found?
- Problem 3: The problem of model calibration. Given an output sequence or a set of such sequences, how can the most adequate set of state transition and output probabilities, $P(O|\lambda)$ be found? In other words, how can the parameters of the HMM be discovered $\lambda = (A, B, \pi)$, given a database of sequences?

About the evaluation problem, problem 1 can be seen as a given model corresponding to a sequence of observations. This problem is solved by the forward-backward algorithm. The most direct way to calculate the probability of the sequence of observations $O=\{O_1;O_2;O_3 \ldots O_T\}$, given the model $\lambda=(A,B,\pi)$, is through the enumeration of all possible sequences of states of size T (the number of observations), through the following expression:

$$P(O|\lambda)=\sum_{S_1,S_2,\ldots,S_T}\pi_{S_1}b_{S_1}(O_1)a_{S_1S_2}b_{S_2}(O_2)a_{S_2S_3}b_{S_3}(O_3)\ldots\ldots\ldots a_{S_{T-1}S_T}b_{S_T}(O_T)$$

The expression involves $(2T*N^T-1)$ that is of difficult calculation, which makes it application not possible without powerful and expensive computer resources. For N=5 and T=100, it would involve about 10^{72} multiplications. We would need a supercomputer to solve the problem. Because of this, the procedure forward-backward is used. The forward variable $\alpha_t(i)$ is the probability of sequence of partial observations $O_1;O_2;O_3 \ldots O_t$, until the state *i*, at the instant *t*, given λ, where $\alpha_t(i)=P(O_1,O_2,O_3,\ldots\ldots,O_t,S_t=q_i|\lambda)$.

Note that,

$\alpha_T(i)=P(O_1,O_2,O_3,\ldots\ldots,O_T,S_T=q_i|\lambda)$.

$\alpha_t(i)$ can be solved using the following expressions:

- Initialization:

$$\alpha_1(i)=\pi_i b_i(O_1),\quad 1\le i\le N$$

- Induction:

$$\alpha_{t+1}(j)=\left[\sum_{i=1}^{N}\alpha_t(i)a_{ij}\right]b_j(O_{t+1}),\ 1\le t\le T-1\ \ e\ \ 1\le j\le N$$

- Ending:

$$P(O|\lambda)=\sum_{i=1}^{N}\alpha_T(i)$$

This procedure reduces drastically the number of necessary calculations.

For the same reason, the backward variable $\beta_t(i)$ is defined as the probability of sequence of partial observations t+1 to the final, given the state *i* at time *t* and the model λ where:

$$\beta_t(i)=P(O_{t+1},O_{t+2},O_{t+3},\ldots\ldots,O_T|S_t=q_i,\lambda)$$

$\beta_t(i)$ can be solved using the next expressions:

- Initialization:

$$\beta_T(i)=1,\quad 1\le i\le N$$

- Induction:

$$\beta_t(i)=\sum_{j=1}^{N}a_{ij}b_j(O_{t+1})\beta_{t+1}(j),\quad t=T-1,T-2,\ldots 1\ \ e\ \ 1\le i\le N$$

- Ending

$$P(O|\lambda)=\sum_{i=1}^{N}\pi_i b_i(O_1)\beta_1(i)$$

In the resolution for evaluation of the problem it is necessary to use only one of the variables, α or β.

Problem 2 tries to discover the hidden part of the model. It attempts to find the correct sequence of states. This problem is, usually, solved using an optimal procedure, called the Viterbi algorithm, which aims to find the best state sequence $S=\{S_1;S_2;S_3 \ldots S_T\}$ for the given observation sequence $O=\{O_1;O_2;O_3 \ldots O_T\}$.

For this objective, the variable

$$\delta_t(i)=\underset{S_1,S_2,S_3,\ldots,S_{t-1}}{máx}P[S_1S_2S_3\ldots\ldots S_{t-1}\ S_t=q_i,\ O_1O_2O_3\ldots\ldots O_t|\lambda),$$

is defined in which $\delta_t(i)$ is the best result (highest probability) along a simple path in time *t*, which accounts for the first *t* observations and ends in state q_i. By induction we have:

$$\delta_{t+1}(j)=[\underset{i}{máx}\,\delta_t(i)a_{ij}]b_j(O_{t+1})$$

To retrieve the state sequence, we need to keep track of the argument which maximizes the previous expression, for each *t* and *j*, through array $\psi_t(j)$. The complete procedure to find the best sequence of states is the following:

- Initialization:

$$\delta_1(i)=\pi_i b_i(O_1),\quad 1\le i\le N$$
$$\psi_1(i)=0$$

- Recursion:

$$\delta_t(j)=\underset{1\le i\le N}{máx}\left[\delta_{t-1}(i)a_{ij}\right]b_j(O_t),\quad 2\le t\le T\ \ e\ \ 1\le j\le N$$
$$\psi_t(j)=\arg\underset{1\le i\le N}{máx}\left[\delta_{t-1}(i)a_{ij}\right],\quad 2\le t\le T\ \ e\ \ 1\le j\le N$$

- Termination:

$$P^*=\underset{1\le i\le N}{máx}\left[\delta_T(i)\right]$$
$$S_T{}^*=\arg\underset{1\le i\le N}{máx}\left[\delta_T(i)\right]$$

Path (sequence of states) backtracking:

$$S_t{}^*=\psi_{t+1}(S_{t+1}^*),t=T-1,T-2,\ldots\ldots,1$$

With the exception of the backtracking step, the Viterbi algorithm and the forward procedure have basically the same implementation. The only difference between them is based on the fact that the sum of the procedure forward is substituted by the maximization in Viterbi algorithm.

Problem 3 is presented as the most difficult to implement. It consists of determining a method to adjust the parameters of the model $\lambda = (A, B, \pi)$, to satisfy a certain criterion of optimization. The sequence of observations used to adjust the parameters of the model is named by the sequence of experimentation because it is used to try the HMM. No analytical process is known to find the group of parameters of the model that maximize the probability of sequence of observations.

However, we can choose the model $\lambda = (A, B, \pi)$, such that the probability, $P(O|\lambda)$, is locally maximized using an interactive procedure, such as the Baum-Welch method, also known as expectation-maximization (EM) method.

To describe the re-estimation procedure for parameters HMM, at the level of iterative actualization and improvement, we define the variable $\xi_t(i, j)$, as the probability of being the system in state q_i, at instant t, and in state q_j, at time t+1, given the model and the sequence of observations

$$\xi_t(i,j) = P(S_t = q_i, S_{t+1} = q_j | O, \lambda).$$

Through the definitions of variables forward and backward, we can write $\xi_t(i, j)$, in the form:

$$\xi_t(i,j) = \frac{\alpha_t(i) a_{ij} b_j(O_{t+1}) \beta_{t+1}(j)}{P(O|\lambda)}$$

$$\xi_t(i,j) = \frac{\alpha_t(i) a_{ij} b_j(O_{t+1}) \beta_{t+1}(j)}{\sum_{i=1}^{N}\sum_{j=1}^{N} \alpha_t(i) a_{ij} b_j(O_{t+1}) \beta_{t+1}(j)}$$

where the numerator term is just $P(S_t = q_i, S_{t+1} = q_j, O|\lambda)$ and the division by $P(O|\lambda)$ gives the desired probability measure.

We define $\gamma_t(i)$ as the probability of to be in state q_i at instant t, given the observation sequence and the model:

$$\gamma_t(i) = P(S_t = q_i | O, \lambda)$$

In these conditions we can relate $\gamma_t(i)$ and $\xi_t(i, j)$ by summing over j, giving:

$$\gamma_t(i) = \sum_{j=1}^{N} \xi_t(i,j).$$

Note that $\sum_{t=1}^{T-1} \gamma_t(i)$ is the expected number of transitions of q_i, and $\sum_{t=1}^{T-1} \xi_t(i,j)$ is the expected number of transitions from q_i to q_j.

In the same way, $\gamma_t(i)$ can be written in function of variables forward and backward by this way:

$$\gamma_t(i) = \frac{\beta_t(i)\alpha_t(i)}{P(O|\lambda)}.$$

Therefore, the calculation of the re-estimation parameters of HMM, π, A and B, of HMM is done through the following expressions:

a) Expected frequency (number of times) in state q_i at time (t=1):

$$\bar{\pi}_i = \gamma_1(i).$$

b) The expected number of transitions from state q_i to state q_j divided by expected number of transitions from state q_i:

$$\bar{a}_{ij} = \frac{\sum_{t=1}^{T-1} \xi_t(i,j)}{\sum_{t=1}^{T-1} \gamma_t(i)}.$$

c) The expected number of times in state q_j and observing symbol V_k, divided by the expected number of times in state q_j:

$$\bar{b}_j(k) = \frac{\sum_{\substack{t=1 \\ \text{For } O_t = V_k}}^{T} \gamma_t(j)}{\sum_{t=1}^{T} \gamma_t(j)}.$$

An important aspect of re-estimation procedure is about stochastic constraints of the HMM parameters, namely:

$$\sum_{i=1}^{N} \bar{\pi}_i = 1$$

$$\sum_{j=1}^{N} \bar{a}_{ij} = 1, \quad 1 \le i \le N$$

$$\sum_{k=1}^{M} \bar{b}_j(k) = 1, \quad 1 \le j \le N$$

If an initial model is defined like $\lambda = (A, B, \pi)$ and its model re-estimated is defined like $\bar{\lambda} = (\bar{A}, \bar{B}, \bar{\pi})$, Baum proved that if the initial model, λ, is in the critical point of the probability, which corresponds to $\bar{\lambda} = \lambda$, or the model $\bar{\lambda}$ is more fruitful than the model λ, in the sense that $P(O|\bar{\lambda}) > P(O|\lambda)$, then we have found a new model, $\bar{\lambda}$, in which the observation sequence is more likely to have occurred.

Based on that procedure, it is used iteratively, $\bar{\lambda}$ instead of λ. The calculation of re-estimation is repeated, allowing the improvement of probability of observations to be reproduced by the model. Some programs calculate the logarithm of probability. In this case, when we detect that, $\ln P(O|\bar{\lambda}) \leq \ln P(O|\lambda)$, we might stop calculation.

The final result of this re-estimation procedure is the occurrence of estimation of the maximum probability by HMM. The algorithm of forward-backward conducts the calculation for a point that is a relative maximum. This fact can lead to errors, because in many problems of practical interest, the probability function is very complex and has several maximums.

In discrete Markov processes another interesting question that can be answered using the model is: Given the system in a known state, what is the probability that it stays in that state for exactly *d* days?

The supposition is that the system is characterized on day *t* by a single state. This probability can be evaluated as the probability of the state sequence:

$$S_{days} = \left\{ \underset{1}{q_i}; \underset{2}{q_i}; \underset{3}{q_i}; \underset{4}{q_i}; \underset{5}{q_i}; \ldots; \underset{days}{q_j} \neq q_i \right\}.$$

This probability is:

$$P(S_{days}|\lambda, S_1 = q_i) = (a_{ij})^{days-1}(1 - a_{ij}) = p_{q_i}(days).$$

The quantity of $p_{q_i}(days)$ is the discrete probability density function or duration "$days$" in state q_i. This exponential duration density is characteristic of the state duration in a Markov chain. Based on $p_{q_i}(days)$, we can readily calculate the expected number of days in a state, q_i, conditioned on starting in that state as:

$$\bar{d}_{q_i} = \sum_{days=1}^{\infty} days.p_{q_i}(days)$$

$$\bar{d}_{q_i} = \sum_{days=1}^{\infty} days.(a_{ii})^{days-1}(1 - a_{ii}) = \frac{1}{1 - a_{ii}}.$$

Although the general formulation was the discrete and continuous HMM, this model is applicable to a wide range of problems.

However, there is another very interesting class of HMM that is particularly applicable to speech processing. This is the class of auto-regressive HMM. For this class, the observation vectors are drawn from an auto-regression process.

4.3.4 Limitations and advantages of HMM

The biggest limitation is the hypothesis that the successive observations be independent, because only in that case the probability of the sequence of observations $P(O_1; O_2; O_3 \ldots O_T)$ can be written like the product of the probability of individual observations. Hence, only in this case it will have

$$P(O_1; O_2; O_3 \ldots O_T) = \prod_{i=1}^{T} P(O_i).$$

The advantages are many, being the main ones the following:

- The HMM have a strong mathematical base, because of the guarantee of convergence for an optimal point;
- It requires a minimum supervision and allows the integration of several levels of knowledge in a unified framework.

4.3.4 The case of urban transport

The research under discussion has the objective to anticipate the diagnosis of engine bus and respective post-treatment systems, using environmental indicators as variables for on-condition maintenance. Under this system we collect data and, aided by MATLAB software, analyse it, being possible to forecast next state and diagnosis dysfunctions. Later, in a second phase, the challenge is to create a wireless network that completes information communication using online measures and data transmission between a control centre and the bus fleet. It is an evolution of a dynamic maintenance scheduling using online information about system condition [34].

This new possibility will be developed in a new module of on-condition maintenance of SMIT. This will permit to plan, to report, to manage resources, as any other module, like above described.

Fig.17 – A Bus of city of Coimbra

Under this research, all types of typical dysfunctions or faults are properly sampled and pre-processed, after they had occurred. At the same time these level of emissions are registered: PM_{10}, NO_x, CO, HC, Noise, Fuel Consumption, Oil Consumption and Engine Head Temperature. Instead the use of viscosity, oil infrared analysis is a promising technique. Infrared thermography is also the methodology used to measure the engine head temperature. Under these conditions, performance vectors associated to a time series modelling can be created.

SYSTEMS UNDER DYSFUNTION	INDICATOR							
	Opacity	NOx	CO	HC	FUEL c	OIL con	NOISE	DTEMP
Glow plug	$\lambda_{1.1}$	$\lambda_{1.2}$	…	…	…	…	…	$\lambda_{1.8}$
Fuel pump	$\lambda_{2.1}$	$\lambda_{2.2}$	…	…	…	…	…	$\lambda_{2.8}$
Injectors	$\lambda_{3.1}$	$\lambda_{3.2}$	…	…	…	…	…	$\lambda_{3.8}$
Turbo-charging	$\lambda_{4.1}$	$\lambda_{4.2}$	…	…	…	…	…	$\lambda_{4.8}$
Feed Governor Regulation	$\lambda_{5.1}$	$\lambda_{5.2}$	…	…	…	…	…	$\lambda_{5.8}$
Distribut. system	$\lambda_{6.1}$	$\lambda_{6.2}$	…	…	…	…	…	$\lambda_{6.8}$
Valves	$\lambda_{7.1}$	$\lambda_{7.2}$	…	…	…	…	…	$\lambda_{7.8}$
Combustion chamber leakage	$\lambda_{8.1}$	$\lambda_{8.2}$	…	…	…	…	…	$\lambda_{8.8}$
EGR system	$\lambda_{9.1}$	$\lambda_{9.2}$	…	…	…	…	…	$\lambda_{9.8}$
Cooling system	$\lambda_{10.1}$	$\lambda_{10.2}$	…	…	…	…	…	$\lambda_{10.8}$
Lubrifica. system	$\lambda_{11.1}$	$\lambda_{11.2}$	…	…	…	…	…	$\lambda_{11.8}$
Control systems	$\lambda_{12.1}$	$\lambda_{12.2}$	…	…	…	…	…	$\lambda_{12..8}$

Fig. 18 - The main models of engine operation range

After normalization, these sets of feature vectors are used as inputs into an HMM of each dysfunction or fault mode for training the models. Once each dysfunction or fault mode is linked with emission level indicators, an HMM model library for each pair of combinations is established; dysfunction mode (DM) or system under dysfunction can be environmental indicators (EI). Under these conditions, it is possible to predict the condition of the set with a maximum probability.

To optimize the model, and with the objective of covering all engine operation range or engine mapping, it is desirable to apply these methodologies to each engine operation region, specifically, each trilogy regimen: Load (*L*); Torque (*T*); and Speed (*n*). Besides this, the number of models under analysis is influenced not only by the dysfunction groups (*d*) but also by selected environmental indicators (*e*). Thus, the number of models to be integrated in a decision to maximize the probability of occurrence, the link between emissions and states, or the association dysfunction-state, is given by the product $L \times T \times n \times d \times e$. Each global model is applied to each bus of the fleet in operation. Being, *B,* the number of buses, this implies that we need $B \times L \times T \times n \times d \times e$ sub-models to identify the better one.

When the operation mode or measure mode is fixed or pre-defined, using the same Load-Torque-Speed, or the same variation of speed, the number of models is reduced to, $d \times e$. To preserve the same variation of speed with constant acceleration on accelerator pedal, a mechanism to actuate on it was built. This equipment imposes the same pressure on the pedal, accordingly the kind of spring. In this context, the main models can be summarized in Fig. 18. The machine condition is identified by selecting the HMM which maximizes the probability of a given observation [35].

In this context, we are integrating 12 groups of dysfunction and 8 environmental indicators in the global model. In other words, we are considering 96 sub-models.

The control systems include, among others, equipments and components: air mass meter, air temperature sensor, air pressure sensor, water temperature sensor, crankshaft position sensor and camshaft sensor; this is considered progress on the evaluation related to the state of the art.

Nowadays, typical families of techniques can be used to predict internal conditions and impeding failures through chemical analyses. Within this context, there are seven basic types of chemical analysis (Fig. 19).

Type	Description
Atomic emission spectrometry	Evaluation of all materials

Atomic absorption spectrometry	Evaluation of all materials
Gas chromatography	Gases emitted by faults
Infrared spectroscopy	Similar to atomic emission spectrometry
Fluorescence spectrometry	Assessment of oxidation products
Liquid chromatography	Lubricant degradation
Thin layer activation	Uses radioactivity to measure wear

Fig. 19 - Types of chemical analysis

The first two are related to particle size and composition.

Oil analysis is a significant subset of all chemical analysis that is used to activate a maintenance intervention. Healthy and clean oil leads to the minimization of machine wear. When abnormal wear is detected the particles are examined by metallurgy techniques (ferrography). The most obvious particle detection technology is the use of a magnetic plug. As an important example of magnetic particle techniques is Eddy Current Testing or Magna-Flux, that is borrowed from automobile racing and racing engine rebuilding. These techniques induce very high currents in a steel part, as the crankshaft or camshaft.

The data collected are used for training each HMM. The time series of collected data correspond to inputs to an HMM for fault classification. Each sub-model includes two kinds of hidden states, the normal state and dysfunction states.

Using MATLAB HMM Toolbox, as an example of "likelystates" function, each defined sub-model, $\lambda_{d.e}$, is calculated through the simulated model sequence states and compared with the sequence of real states. In addition, the probability $P_{d.e}$ of estimated states to overlap to real states is calculated. In other words, the model calculates the probabilities of estimated states corresponding to the real states.

REAL_EMIS	O_1	O_2	....	O_k
REAL_STATE	S_1	S_2	....	S_k
EST_STATE	S_i	S_j	....	S'_k
Probability	$P_{d.e}$			

Fig. 20 – Outputs of each sub-model

In figure 20, REAL_EMIS are the observed emissions; REAL_STATE are the real states, and EST_STATE are the model estimated states.

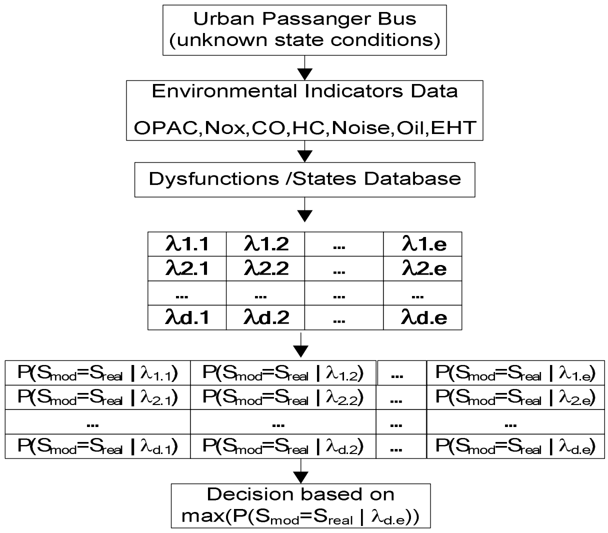

Fig. 21 – HMM transition states

$P(S_{mod}=S_{real}/\lambda_{d.e})$ is the probability of a model state to overlap the real state.

5 Integration of Modules

5.1 Computing

Fig. 12 represents the SMIT system. The system has client/server architecture.

The server is based on Linux [16] and a Desktop/Laptop client for windows environment [15]. The Linux server incorporates the following functionalities: database PostgreSQL [17]; web [18], [19], fax and email server [16]; a TCP/IP server for reception of data acquired from different acquisition points; SNTP/NTP Server; SNMP [32] and *ftp* server. To dialog with other applications, the system supports insert/update/delete using web services technology and also import/export in csv/xml format. The system is very portable; it can run on Windows/Unix/Linux/Mac OS, if and only if PostgreSQL and PHP are available.

5.2 The local and national databases

In the earlier point the use of web services technology was focused. This is an enormous advantage to implement some solutions, for example:

- A national database for fault diagnosis;
- A national database for spare parts;

- Local database for work orders, technicians and so on, but working in connection with national databases.

Having a national and local database enables relevant information to be shared among different clients to give support in detecting the source of faults, and so on. However, specific data should not be shared, like costs, suppliers, working orders, and planning policy. Web services make this task very easy. About these subjects see also [36].

One example of this methodology is under the Wind Turbines Maintenance, where many relevant data can be inserted in a national database, like types of faults, the way to solve them, maintenance indicators, like MTBF, MTTR, and so on. This is important not only to share knowledge (considering any worry about company competitions), but also to plan the produced power and risks to fulfill expected wind production (by failure or no wind).

Another important situation where this approach is relevant is in hospital field because the importance of many equipment, namely the life support and others in general. The diversity of suppliers, the price of equipment and spare parts, the small number of some equipment, the location of some suppliers of maintenance services and many other singular situations, are reasons enough to consider the hospital equipment a case study for the approach behind referred.

```
<?php
require_once('libSOAP/nusoap.php');
$wsdl="http://smitserver.pt.pt/smit/
            webservices/serverSOAP.php?wsdl";
$client=new soapclient($wsdl, 'wsdl');
if ($client->getError()) {
   echo '<h2>Client Error </h2><pre>' .
     $client->getError() . '</pre>';
   die(0);}

$param=array(
  "database"=>"smit",
  "login"=>"adm",
  "passwd"=>"adm",
  "sql"=>"select * from
          insertom_p15('parameters');");

$lv_value=$client->call('runSQL', $param);
if ($client->fault) {
            echo '<h2>Fault</h2><pre>';
            print_r($lv_value);
            die(0); }
if ($client->getError()) {
  echo '<h2>Error calling functionx</h2><pre>'
     . $client->getError() . '</pre>';
  die(0);}

echo $lv_value . "<br>";
 // returns from SQL function insertom_p15:
  //   'OK' – update done,
  //   'OK-INS' – First insert
  // By default, the service returns the following values
  // -------------------------------------------------
  //   'ERROR: 1' – No permissions to run the SQL
  //   'ERROR: 2' – Database connection failure
  //   'ERROR: 3' – The user does not exist
  //   'ERROR: 4' - Error running SQL
 print_r($lv_value);
 ?>
```

Fig. 22 – WebService example to run queries from third party software against SMIT database

To include new modules in SMIT is very easy; because the framework is developed in Delphi for windows client/server architecture and for web development Symphony PHP Web Framework. The database is documented in web pages (every table and field, expected values, etc). The module to receive data from field measurements is fully configured in the database (number of clients, sockets to receive data, acquisition method, etc).

Nowadays almost one hundred of on-condition techniques are known and many others could be developed. It is because of this that SMIT was developed with an architecture that can support new modules, namely for predictive maintenance. But this integration is not a sum of more modules but a real integration where each new on-condition component dialogues dynamically with the main modules, like planning and work orders, among others.

The new predictive modules can receive data through keyboard, PDA, specific tools, like thermographic cameras, noise meters, or on-line acquisition. This makes SMIT not only a maintenance management system but an asset management system and a system that makes this management available 24 hours a day, and an alert system for the complete accompanying of behavior of equipment and systems.

6 Further Developments

Based on this point of development, where the maintenance management system was enriched by two new areas, namely the SMIT, there are also new opportunities to improve, namely:

- New maintenance methodologies for general combustion engines;
- New on-condition modules;
- The increase of life cycle of vehicles based on its transformation through the implementation of new technologies;
- Renewal methodologies for equipment in an environmental approach;

- Withdrawal of equipment in an environmental approach;
- Improvements based on new approaches based on fuzzy theory;
- Integration of SMIT with other software tools for a general management in any organization;
- Risk analysis in the several areas of asset management.

7 Conclusion

When equipment is in pre-dysfunction state it sends out signals or symptoms that are not within the perception range of human senses. To search for an early detection of these signals, techniques that enable to model and predict environmental effects, like emissions, including noise effects, oil degradation and infrared thermography, are an evolution in the direction of ecological predictive maintenance.

Several of these techniques have their limitations. However, in certain applications they are the best choice.

In this article a maintenance strategy applied to a renewable energy was presented and also a new way to manage the planned maintenance of diesel engines based on environmental parameters.

The developed software SMIT that is totally stabilized at the present date is a powerful tool for maintenance management and is used as the background for these new developments.

Because the tendency in the future is to use typical house/industrial equipment that includes a communication network like ZigBee (now with a great expansion in the area of wireless sensors), the inclusion of a new software module for on-condition monitoring based on on-line instrumentation is relevant. The paper points out a methodology that is under development.

Additionally, the equipment sends out signals or symptoms that are usually not within the perception range of human senses but can translate environmental dysfunctions. The accompanying and forecasting based on these signals, like effluents from emissions, noise, oil degradation and temperatures, aims to manage on-condition maintenance approach in an ecological way. The model presented in this paper for predictive maintenance uses Hidden Markov Models and the results are promising.

We think this is a way to contribute for a new world.

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