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CBM for a fleet of railway vehicles: infrastructure and algorithms

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ABSTRACT
Data acquisition and communication technologies give the possibility of receiving and storing a huge amount of data from machinery and plants in operation. From these data it is possible to create a set of Key Maintenance Indicators (KMI) useful for optimizing the maintenance policy. Raw data from the field are to be processed and filtered for obtaining effective KMIs to use in algorithms aimed at discovering anomalies or abnormal operation of one or more machineries or plants.
This paper presents a roadmap towards the Condition Based Maintenance of a fleet of railway vehicles. The paper associates to each maintenance policy its benefits and its requirements in terms of technological infrastructure and operating costs. Bombardier Transportation Italy started this roadmap a few years ago, for moving from a reactive maintenance policy to a proactive policy.
Increasing the effectiveness of maintenance implies the sensorization of the machines and the creation of a network for funneling information from the machineries to the central maintenance room. A Company must find an equilibrium point between complexity and expected benefits.
Results achieved by means of a specifically developed tool for data analysis applied to some sub-systems of the vehicles are presented.

Section: RESEARCH PAPER

Keywords: railway vehicles; Condition Based Maintenance (CBM); key maintenance indicators; condition monitoring; industrial communication

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1. INTRODUCTION

Optimizing the maintenance for a fleet of machineries or vehicles means to guarantee a high Quality of Service (QoS) with a minimum number of interventions. The concept of QoS varies for each specific application. For railway vehicles, the passengers that want to have reliable trains on time measure the QoS. For machinery, QoS means almost often to work without interruptions and with a constant quality of the production. In all cases, the QoS is related to the availability that is the percentage of time a system is in normal operating conditions.

An optimized maintenance strategy coordinates the scheduled stops with the maintenance interventions, e.g. railway vehicles must stop for safety reasons a fixed number of times per year or after a given number of kilometres according to national regulations and laws. Maintenance policies are discussed in [1]-[9].

Condition Based Maintenance (CBM) and Predictive Maintenance (PM) seem to be the most effective policies, since their goal is to start a maintenance intervention only when it is necessary. To do this, it is mandatory to monitor the operation of a vehicle (or a machinery, or a plant) to find symptoms of incoming failures ("fix it before it fails"). For this purpose, various metrics and sensor-based methods can be used to measure and monitor continuously the condition of the equipment. To do this, we introduced the concept of Key Maintenance Indicator (KMI) that may represent:

- a simple counter of variables of the vehicle (e.g. distance travelled, hours of operation, the number of times a door opened and closed, etc.;

- a calculated variable that uses different parameters of the vehicle (e.g. number of occurrence of "X" when "Y" was on, etc.);

- measures from sensors (e.g. oil analysis, vibration analysis, etc.) specifically installed for maintenance purposes.

The KMIs are the foundation for the construction of algorithms aimed at monitoring the status of the vehicle and at deciding maintenance interventions [11], [12].

Collecting and processing the raw data that will become KMIs require a complex technological infrastructure described into details in [10]. Railway vehicles require two sub-systems:

- "on-board system" (the train): that produces and collects raw data and sends them to the;

- "off-board system": collects data from all the vehicles and implement the algorithms for CBM.

This paper shortly describes the on-board and off-board infrastructures, and focuses on the procedures for the data analysis and for the discovery of rules and metrics useful for CBM; in other words, the "Conditions" to active a maintenance intervention. A joint research team of Bombardier Transportation Italy and of the University of Genoa, Dept. DITEN, developed a tool for the data filtering, sorting, and analysis that was applied on the historical database of about 5000 vehicles to find rules for deciding the maintenance interventions. The paper presents some results of this analysis for three different sub-systems.

2. THE TECHNOLOGICAL INFRASTRUCTURE

2.1. The on-board infrastructure

Railway vehicles are composed by a set of independent subsystems, each one equipped with a dedicated Train Control & Management System (TCMS) that collects data both for control purposes and for diagnosis. All the TCMSs communicate via the Multifunction Vehicle Bus (MVB), standardized in IEC 61375-3. TCMSs transmit the process data for the vehicle control with a sampling time of 1 second. When a TCMS detects an anomaly, a Diagnostic Data Set (DDS) is generated. The On Board Database Server (ODBS) stores both process and diagnostic data. All data are transmitted to the off-board servers with their time-stamp every two hours. In case a proper transmission channel is not available, data are stored and transmitted when a connection is available.

It is possible to implement some simple KMIs (mainly counters) directly in the TCMSs.

2.2. The off-board infrastructure

The off-board infrastructure consists of a powerful, redundant server that collects the data from all the ODBSs of the fleet. A software package, called Maintenance Software Package, makes data from the trains available to all the users.

The maintenance staff should:

- monitor the fleet;
- detect and prevent faults and anomalies;
- define the maintenance work schedule.

The maintenance staff is coordinated with the various Regional Operation Rooms.

3. MAINTENANCE POLICIES

As explained in [10], with CBM an equipment is maintained only when it needs maintenance, so no unnecessary intervention is carried out. An effective CBM requires reliable data from the trains and powerful algorithms for their analysis. Effectiveness of maintenance evolves together with the evolution of the technological framework of the Company. For sake of simplicity, we split this evolution into four steps:

- Reactive Maintenance: it includes cyclic interventions and overhauls during the stops at the depot. No train-ground data transfer is required;

- Remote Maintenance: the maintenance staff can access the ODBS for monitoring the status of each vehicle. Alarms are received real-time;

- Reactive Maintenance: the maintenance staff uses rules and algorithms for monitoring the trains and communicates with the on-board personnel in case of detection of anomalies. Maintenance schedule is dynamically updated;

- Condition Based Maintenance: KMIs and algorithms are used for calculating the residual life of components.

A cost/benefit analysis is necessary for deciding to switch from one step to a higher one.

4. DATA ANALYSIS FOR CBM

Techniques of Data Mining are useful for analysing the large amount of data from the trains stored in the centralized database. Data mining means to extract useful information hidden in the data and to present them in the more simple and usable ways. Data mining methods use statistical approach and different mathematical techniques suitable for managing data and database to look for correlations.

Essentially, a database for CBM purposes contains in the rows different objects - in our case different vehicles of the same fleet - and in the columns the properties and the parameters describing the behaviour of the object (see Figure 1). A typical locomotive has about 2000 operating parameters, split between about 10 major subsystems. A subset of these parameters may give useful information for maintenance purposes. The case histories at pos.5 show some examples of maintenance-related parameters for specific subsystems.

Considering such a database structure, it is possible to define three possible approaches to the data analysis:

- Horizontal: analyses the same property of different

Vehicle	#1	#2	#3	…	#m
Parameter #1	p_{11}	p_{12}	p_{13}	…	p_{1m}
Parameter #2	p_{21}	p_{22}	p_{23}	…	p_{2m}
Parameter #3	p_{31}	p_{32}	p_{33}	…	p_{3m}
…..	…	…	…	…	…
Parameter #n	p_{n1}	p_{n2}	p_{n3}		p_{nm}

Figure 1. Example of CBM oriented database.

vehicles;

- Vertical: analyses different properties of the same vehicle;

- Mixed: it is a mix of the previous approaches, i.e. different properties of different vehicles or of each single vehicle.

Each analysis is useful for achieving specific results, as described in the following paragraphs.

For each analysis, it is important to define the KMIs of interest.

4.1. Horizontal analysis

Horizontal analysis allows checking and comparing the behaviour of a single vehicle/apparatus/subsystem with the other elements of the fleet. Therefore, the analysis may identify the vehicles with abnormal behaviours in the fleet.

KMIs for comparative horizontal analysis should highlight the overall status of the machine, like the total number of stops, the average consumption, etc.

The first and easiest horizontal analysis is the calculation of average values (xavg) and variances (σ). Machines with parameters outside the average value of the fleet with a band of, for example, $\pm\sigma$ or $\pm 2\sigma$ become candidates for a more accurate and precise analysis. Considering random failures, we can assume a Gaussian distribution of the samples. The level of confidence for setting the alarm threshold for each parameter is set according to the sample distribution.

Considering the example in Figure 2 over 10 vehicles, it is apparent to understand that machine 4 and 9 show an abnormal behaviour.

4.2. Vertical analysis

Vertical analysis considers the behaviour of a vehicle/subsystem over the time. Thus, this analysis shows the upcoming of abnormal behaviour or degradation of a parameter. Different approaches exist for the vertical analysis:

- Trend analysis: is the study of the behaviour of a KMI over the time that may identify a deviation from the expected trend (see Figure 3). The alarm threshold is set on the difference between the current value and the linear regression of the historical data;

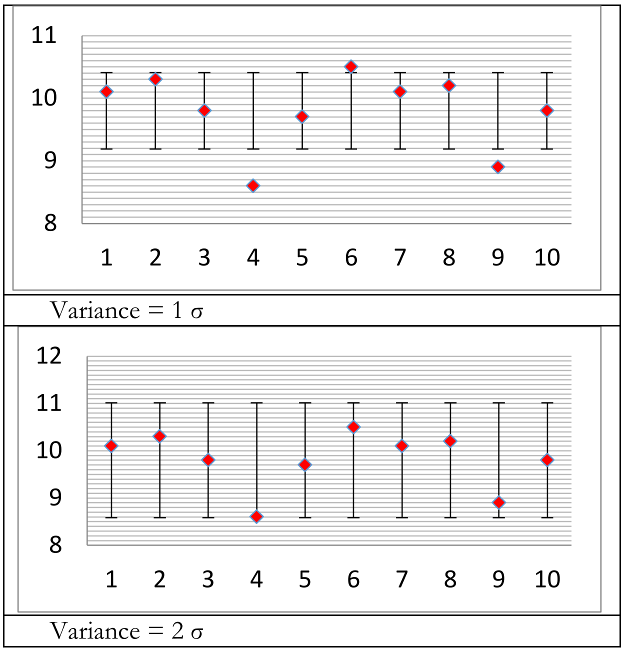

Figure 2. Example of variance analysis.

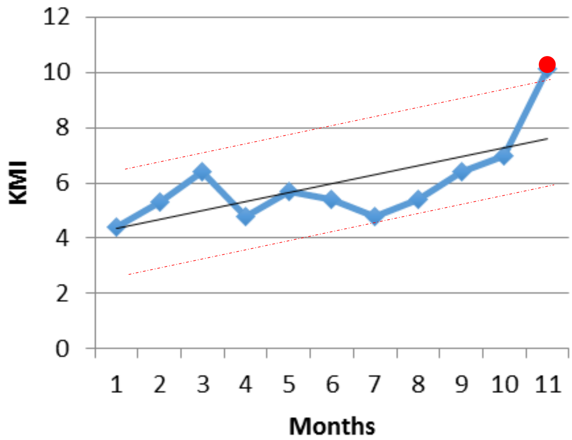

Figure 3. Example of trend analysis.

- Anomalies analysis: with a long-term monitoring, it may identify anomalies in the behaviour of a KMI, like sudden changes or abnormal operations;

- Statistical analysis: it may identify abnormal deviations in the historical behaviour of a KMI;

- Signature analysis of a device: the signature of a device is the set of values that significant parameters of a machine or a system have in normal operating conditions or during the execution of a normal operation. Deviations from the signature indicates abnormal operations. Figure 4 shows an example of signature for a pneumatic actuator using the profile of the output pressure during an open/close cycle.

4.3. Mixed analysis

The mixed analysis may consider different parameters of the same machine/system or also different parameters of different machines. The main scope of the mixed analysis is to identify correlations between different parameters or events.

The basic techniques used for the mixed analysis are:

- Regression: it is necessary to find a formula that expresses the relation between different selected variables;

- Correlation: an index quantifies the correlation between two or more variable. Several indexes exist for measuring the degree of correlation of different variables. One of the most used index is the “Pearson correlation index”. The research of correlation indexes requires the comprehension of the physical relations between the variables (to avoid incongruous results).

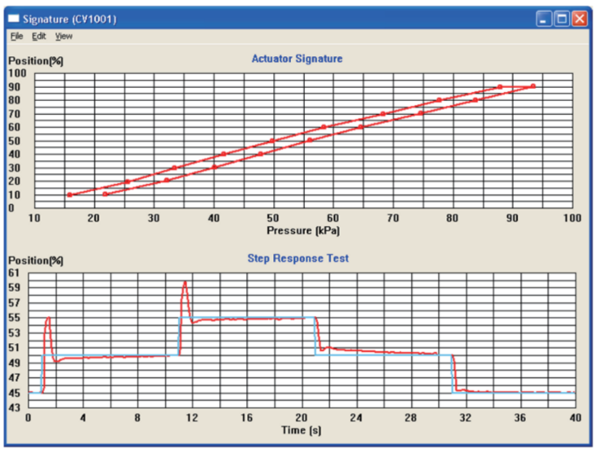

Figure 4. Example of signature for a pneumatic actuator.

5. A CASE HISTORY: BOMBARDIER TRANSPORTATION ITALY

5.1. A short history

This paper describes the evolution of maintenance for two very popular locomotives: model E483 and model E186 that run in almost all the European countries. Both vehicles today have a technological structure that allows the implementation of Remote Maintenance. Process and maintenance data are collected on-board, and are fully accessible by the maintenance staff. Both locomotives started about ten years ago from a status of simple reactive maintenance, and the implementation of on-board and off-board infrastructures was therefore necessary to achieve Remote Maintenance.

Today all vehicles are equipped with a diagnostic controller that collects all the diagnostic data and sends them to an Ethernet gateway that communicates with the off-board system via GPRS. Similarly, the controller of each sub-system on board collects and transmits all the process data, including environmental data like position, speed, ambient temperature, etc.

The control centre in Vado Ligure downloads these two databases through the GPRS modem and makes data available to maintenance staff through the web portal MyBTFleet. For safety reasons, national rules or laws make a maintenance stop for each vehicle mandatory at fixed schedule (e.g. in Italy every 6 months). Through CBM techniques the maintenance operators can define the list of maintenance activities (not safety related) to schedule at a given stop.

5.2. Actions towards Condition Based Maintenance

For increasing the level from Remote Maintenance to CBM, it was necessary to implement a system for the graphical display of the diagnostic data stored in the database to give to the Maintenance Staff an immediate view of the evolution of every parameter. A specific tool for the intelligent data sorting and visualization was created with Matlab. Figure 6 shows an example of graphical output for digital variables. Maintenance engineers may use this tool for soting variables using:

- a defined period of time,
- the ID code of the variables,
- the sub-system,
- the status (e.g. show the variables that were "OFF" in the period from x to y).

The tool can also calculate simple KMIs like:

- counters (in a defined period of time),
- conditioned counters (e.g. operating time with Variable X "ON" and Variable "Y" greater than Z),
- statistics for each signal or group of signals (number of positive or negative transitions, time ON/OFF, etc.).

More complex techniques of data mining are possible, but the size of the database suggests prudence. The monitored vehicles are about 150, and the considered parameters are about 500 for each vehicle, with a sampling time of 1 second (data transmission is only by exceptions).

The next three examples refer to the Bombardier fleet of vehicles, and represent:

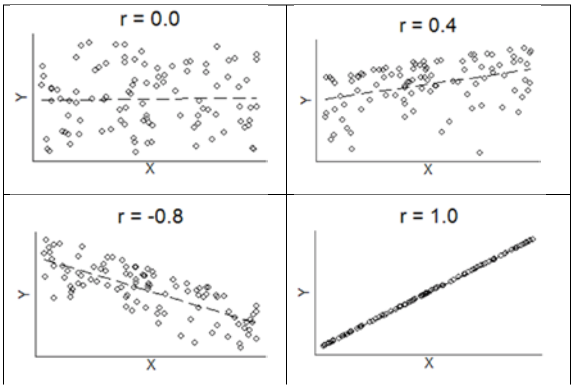

Figure 5. Example of correlation between different variables.

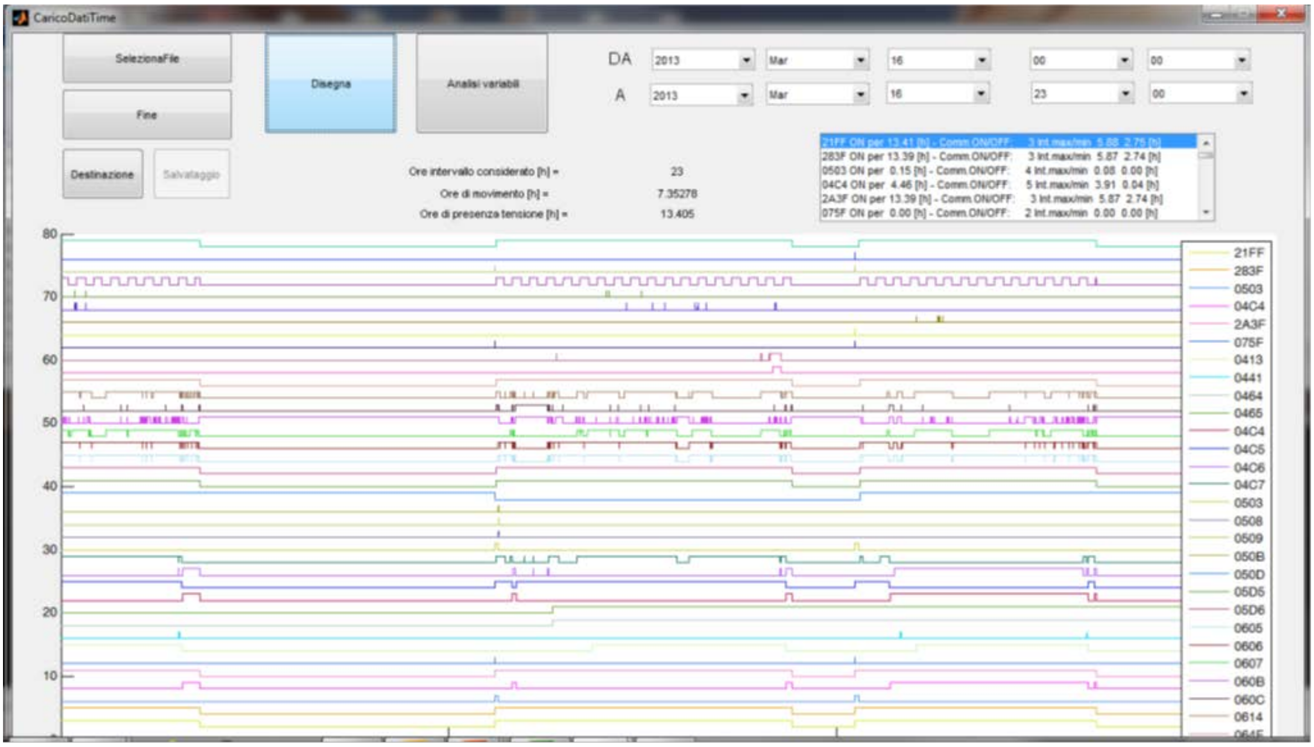

Figure 6. Sample display of the visualization tool.

- a horizontal analysis for the identification of CBM rules for the main circuit breakers,

- a vertical analysis based on the signature for the air compressor on board,

- a complex analysis of multiple measurements of the wheels consumption for determining their expected end-of-live.

The manufacturers of the MCBs consider an average number of operation equal to 1000 after two year, and of 4000 after 8 years. Figure 7 and Figure 8 show that the Main Circuit Breaker of all the locomotives have a much lower number of operations (both AC and DC).

5.3. Rules for CBM: Main Circuit Breaker

The Main Circuit Breaker (MCB) connects the locomotive to the supply line, and it is one of the most critical components. The MCB may be either DC (code "IR") or AC (code "IP"). The MCB is an electro-mechanical equipment enduring both mechanical and electrical stresses. We used the historical database of the fleet for analysing all the failures of the MCBs looking for KMIs related with the failures. This phase of the study uses the knowledge of the equipment. In other words, we pre-selected a subset of data according to the knowledge we have of the construction and operation of circuit breakers to reduce the variables of the problem. The following KMIs proved to be useful:

- KMI#1: counter of normal opening/closing operations of the MCB (with no current);

- KMI#2: counter of MCB trips (the MCB opens the short circuit current);

- Condition#1: train speed > 3 km/h (the train is not in a station);

- Condition#2: status of the pantograph (open/close).

We carried out a mixed analysis in search of correlations on the entire fleet of locomotors E186 for the year 2013 that is 55 vehicles for about 11 months (a locomotive remains in the depot for about 1 month a year).

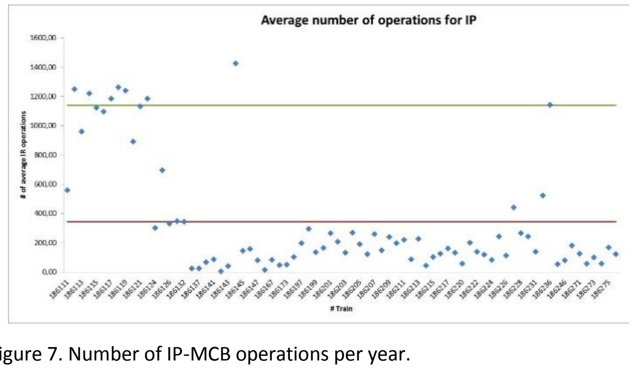

Figure 7. Number of IP-MCB operations per year.

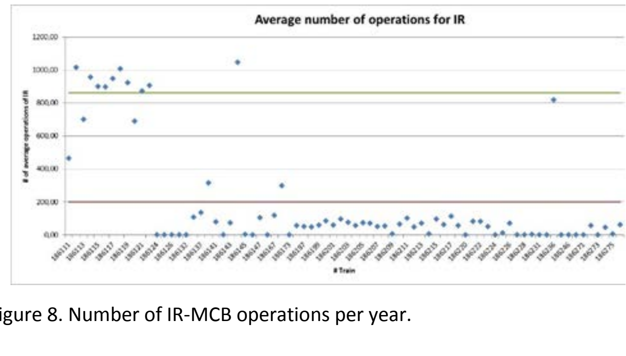

Figure 8. Number of IR-MCB operations per year.

The two KMIs are further split into two classes using Condition#1. When the pantograph is open (condition#2), the counter is not increased.

The average value of these KMIs per month, together with their standard deviation was calculated to find out vehicles with abnormal values. Through the study of the maintenance record of these vehicles, we invented the following heuristic rule:

IF (KMI#1 average per month > 3.5)

AND (KMI#2 average per month > 3.5)

THEN (maintenance is required)

No vehicle with smaller KMIs experienced any failure of the circuit breaker. On the other hand, 33 out of 100 circuit breakers with higher KMIs did not experienced failures. The proposed heuristic rule gives the following results:

- number of maintenance interventions per year:
  . with remote maintenance 55
  . with CBM rules 15

of which 10 necessary and 5 unnecessary.

The application of the rule on the fleet of vehicles for one year of operation reduces the number of unnecessary interventions from 45 to 5 and does not cause any missing maintenance for the MCBs that really need it.

5.4. Rules for CBM: Air Compressor

The air compressor in a locomotive is an essential part of the braking system. The compressor has two output sections that supply the main braking circuit at a rated pressure of 10 bar, and the primary circuit at 5 bar. Pressure losses happen when the brakes operate and for the normal leakages of the circuits. The compressor is controlled in on/off mode by a pressure switch with a hysteresis of 0.05 bar around the rated value. Typically, manufacturers of compressors for railway applications suggest a complete revision after 12,000 working hours (cyclic maintenance).

To have a more accurate maintenance indicator the "signature" of the compressor was defined. When the train runs in normal coasting between two stations, the leakages of the circuits cause the pressure losses. The compressor compensates these losses and maintains the pressure in the range of 4.95-5.05 bar. The horizontal analysis of data shows that the recharging time during the coasting phase for a new compressor lays between 60 s and 70 s. Longer periods, in a reasonable percentage, should be an indicator of an overcoming problem in the compressor, mainly due to malfunctioning of the bearings.

The following quantities are sampled every second:

- Date and time
- Speed
- Pressure in the main pipes
- Pressure in the principal pipes
- Running kilometres

Data were collected for a period of two months on the fleet of 186 locomotors in The Netherlands.

We identified the "signature" of sound compressors and used it as a benchmark for finding out compressors with abnormal operation. The term "signature" refers to a set of measurement or quantities that identify the behaviour of a given component.

The proposed KMIs for the compressors considers:

- the overall average duration of a "on" period for the compressor,

- the average duration of a "on" period for the compressor during coasting,

- the load cycle of the compressor when the train is running (percentage of time "on" compared with the total running time).

Figure 9 shows a typical profile of the air pressure during normal operation of a train. Pressure (blue line) increases when the compressor is running (red line), and it decreases when the compressor is off. Coasting is detected considering the train speed (light blue line); when it is constant the train is coasting, and pressure losses are only caused by the pipes leakages. Pressure variation during braking phases depends on the action of brakes, and are not related with the compressor status.

When the three KMIs that compose the signature are listed in a table like in Table 1, some anomalies can be detected.

As Table 1 shows, compressors work during the coasting phase an average time of about 70 s. A longer time and an increase of this time over different periods may identify an upcoming problem of the compressor. On the other hand, Table 1 shows that the average value of the working percentage of the compressor is around 25 %. Again, values higher than the average may indicate that a failure or a malfunctioning of the compressor is approaching.

For this analysis, we consider the average value and the standard deviation σ to identify the elements or vehicles that show an abnormal behaviour.

Considering the normal distribution and the standard deviation, Table 1 points out two vehicles that have a very abnormal behaviour: locomotive 186113 and 186144.

The main pipe recharging time, during the coasting phase, is a good indicator of the compressor performance. It is plain that the performances of E186113 and E184144 have a completely different behaviour from the other vehicles of the fleet, and an accurate check of these compressors during the next maintenance stop is scheduled.

As all the compressor manufacturers indicate, another important parameter for maintenance purposes is the total working hours of the compressor. Typically, a complete overhaul is recommended after 12,000 working hours.

Considering the average daily mileage and the effective percentage of working hours, it is possible to estimate the total worked hours for each compressor, and to evaluate when it will reach the target of 12,000 hours.

Table 2 shows the estimated end-of-life calculated for the compressors under analysis. With the present usage rate, the

Table 1. Comparison of KMIs for different locomotors.

#Vehicle	Avg Time ON	Avg Time on coasting	Avg % operation	# Samples
186111	90.83	74.48	25.30 %	6
186112	122.91	73.98	30.05 %	4
186113	213.59	126.45	48.46 %	6
186114	73.81	64.47	18.58 %	4
186115	75.49	59.74	16.98 %	14
186116	68.27	54.39	16.13 %	4
186117	88.11	71.74	25.36 %	8
186118	75.79	60.09	22.77 %	8
186119	76.03	60.17	18.64 %	9
186120	77.69	64.45	22.42 %	10
186121	90.03	75.18	26.03 %	6
186122	89.81	67.35	26.89 %	3
186144	121.95	92.87	32.81 %	5
186236	76.05	63.22	21.81 %	5

Table 2. Estimated remaining life of the compressor.

# Vehicle	Daily working hours	Est. Remaining life [years]
186111	4.44	7.41
186112	4.54	7.25
186113	9.08	3.62
186114	3.38	9.72
186115	3.07	10.72
186116	1.90	17.27
186117	4.58	7.18
186118	3.79	8.68
186119	3.12	10.54
186120	4.23	7.77
186121	4.16	7.89
186122	4.30	7.64
186144	5.25	6.26
186236	3.39	9.70

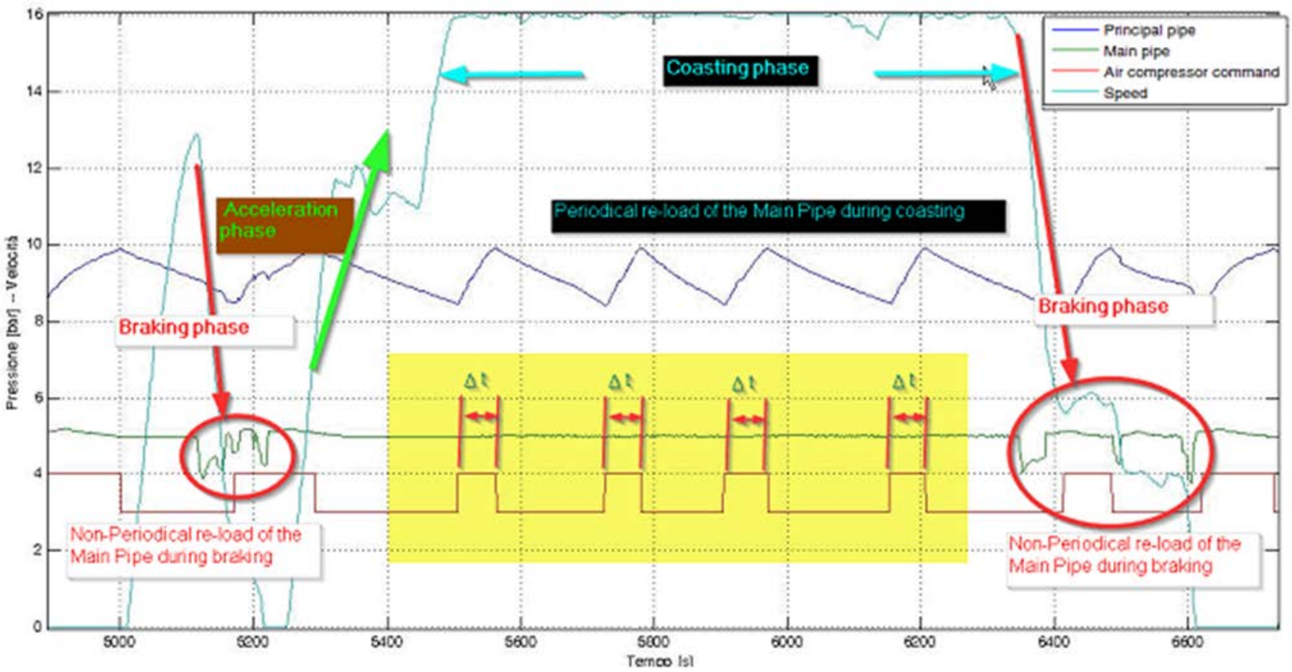

Figure 9. Typical profile of pressure and compressor operations.

compressor of vehicle 186113 will reach the target working hours in 3.5 years, so it has to be the first to be overhauled.

5.5. Rules for CBM: Wheel Profile Monitoring

When a locomotive enters/exits the depot, the Automatic Vehicle Inspection System (AVIS) collects data using laser, thermal and optical imaging technologies. Data are stored and analysed and, when necessary, AVIS generates alarms and automatic maintenance orders (see Figure 10).

The two main parts of AVIS are:

- VEMS (Vehicle Equipment Measuring System) that includes all the sensors, lasers, and cameras that generate the raw measurement data;
- ORBIFLO: the Bombardier software platform that analyses the data for assessing the health status of the vehicle and for implementing rules for maintenance.

Figure 11 shows VEMS, a modular system that contains the following modules:

- axle end temperature monitoring system; it measures the dimensions and temperatures of axes;
- brake pad monitoring system: it measures the thickness of every brake pad, calculates brake pad wear rate and predicts when replacement is due;
- brake disc monitoring system: it measures the brake disk thickness, the disk profile and its maximum wear depth;
- wheel profile monitoring system: it measures the wheel profile and assess condition in comparison to several key markers (flange height, thread hollow, etc.);
- pantograph wear monitoring system: it checks the carbon strip profile, its maximum wear depth, and localized chip size;
- wheel damage monitoring system (WDMS): it measures flat spots on wheels and determines when a wheel must be re-profiled by means of thresholds on the various measures;
- visual image capture system: through laser scanning and optical imaging, it captures many data points of the train exterior, permitting verification of any deviation from the vehicle profile or previous vehicle condition. It is possible to measure the car height, coupler height, to detect missing or displaced elements, open equipment boxes, foreign bodies, etc. It also detects and assesses damper leakage conditions and vehicle contamination (oil leakage, impact damage, graffiti, etc.).

The study that we carried out uses the data of the wheels of a British fleet composed of 302 trains measured and collected by AVIS. Measurements on each vehicle include 16 wheels; 8 right wheels (RHS) and 8 left wheels (LHS).

The analysis considers the following wheel parameters (see Figure 12):

- diameter of the wheel;
- flange height;
- flange thickness;
- difference between the right wheel's diameter and the left one;
- tread hollowness.

To facilitate the data analysis, the data management system of Figure 13 was created. A server runs OSISoft PI analysis software composed by PI Interface, PI Data Archive. The users are client of the PI server, and run PI Processbook and PI Datalink for visualizing the data, together with Matlab for implementing the researched maintenance algorithms.

The combined use of PI Processbook for the dynamical graphic representation of the variables of more wheels simultaneously (Figure 14), together with specific analysis developed in Matlab environment, made it possible to find out a formula for predicting the lifespan of the wheels:

$$Lifespan = \frac{TI}{365} * \frac{D_{max} - D_{min} - {}^{(TI * D_{degr})}/_{365}}{{}^{(TI * D_{degr})}/_{365} - \Delta D}. \qquad (1)$$

With conventional Preventive Maintenance policy, wheels

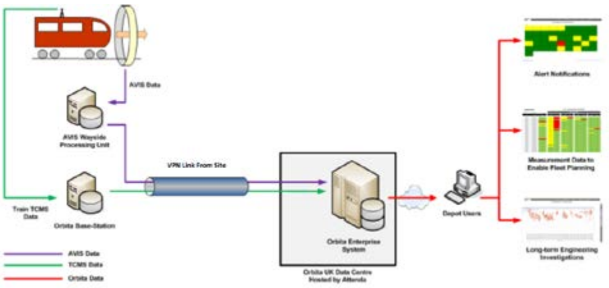

Figure 10. The AVIS Block Diagram.

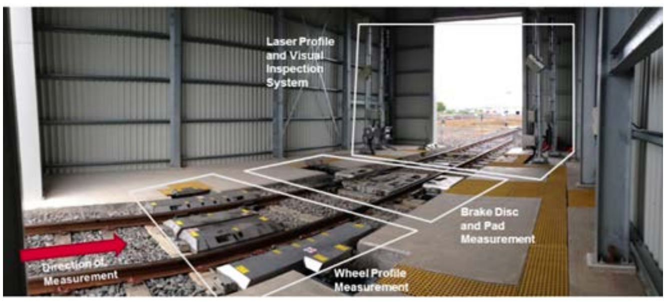

Figure 11. Vehicle Equipment Measuring System (VEMS).

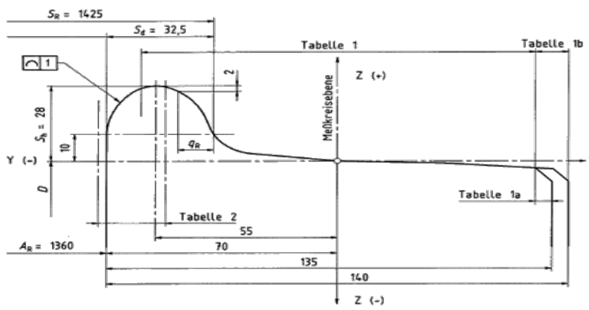

Figure 12. Wheel profile.

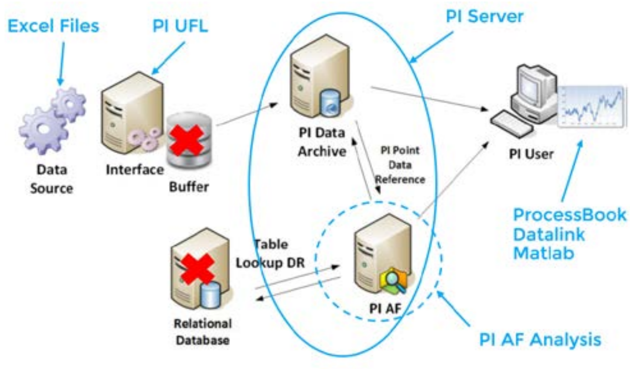

Figure 13. Data Management System with OSISoft.

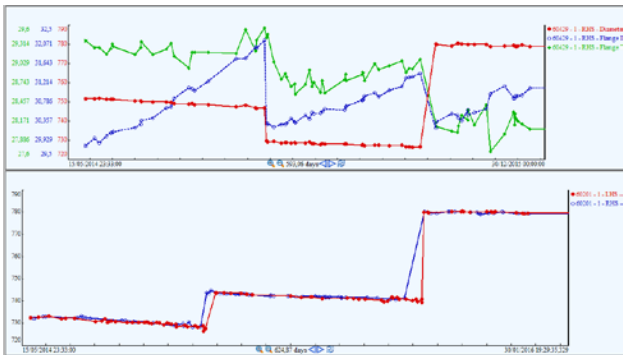

Figure 14. Top: Diameter, Flange Height and Flange Thickness trends of the same wheel; Bottom: Diameter trends of two different wheels.

are re-profiled every 200 or 300 days, according to the region the vehicle works in. With a policy of CBM, the analysis showed that it is possible to calculate the remaining useful lifespan of a wheel starting from the values collected by the WDMS. Interpolating the available values, it is possible to predict when a wheel will run out of tolerance (see Figure 15).

This algorithm may reduce the maintenance interventions for the vehicle wheels of about 10 %. Its application just started few months ago, and sufficient data are not yet available for evaluating its effectiveness.

6. CONCLUSIONS

Maintenance is one of the higher costs for a Company that controls a fleet of vehicles. On the other hand, maintenance has an important effect on the Quality of Service of the same Company. An intelligent maintenance policy has positive effects in terms of both costs and QoS. In the paper we propose a roadmap that may lead a Company from a cyclic maintenance policy (either costly or ineffective) to Condition Based Maintenance (maintenance only when required). Increasing the effectiveness of the maintenance requires a technological infrastructure for on-board data collection and transmission to a ground maintenance centre where data are stored and analysed.

Raw data from the vehicles are to be processed and grouped into Key Maintenance Indicators (KMI) that become the basic elements to use for maintenance-oriented algorithms. The identification of KMIs for a device or sub-system is based on two milestones:

Figure 15. Flange Thickness (red line), its linear regression (blue line) and its limits (green and pink lines).

- the technical knowledge of the construction and operation of the device or sub-system to find-out a set of parameters that may be useful for maintenance purposes,
- the analysis of the historical database for cross-correlating the candidate KMIs and the behaviour of the device or sub-system.

The paper shows three examples of this analysis:
- the KMIs and the rule for deciding when the Main Circuit Breaker of locomotive has to be maintained;
- the KMIs and the rule for understanding when the air compressor of the locomotive need an intervention. A rule for calculating the expected end of live is also presented;
- a real-time data analysis structure for the calculation of the wheel consumption and the prediction of the necessity of their re-profiling.

These rules are implemented on line, and are used for sending automatic maintenance warnings to the maintenance staff.

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