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Development of Condition-based Maintenance Control Systems in Fleet Management activities

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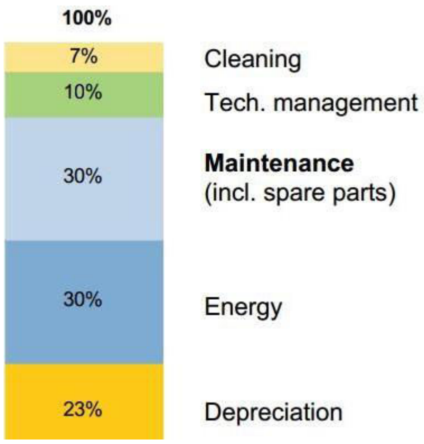
Abstract: *The advancement in the domain of big-data technologies and machine-to-machine (M2M) interconnectivity is creating new possibilities for real-time analysis of machine components for identifying and avoiding breakdowns. Designing of such environment with a high-speed fleet requires special attention to the design methodologies used in collecting the operating requirements from the users and transforming it into big-data parallel architectures is one of the crucial task.This transformation can lead to provide the capability of exhibiting fault-tolerant behavior and load-balancing features. This paper describes the 3 M2M approach for the big- data condition-based maintenance system and the requirement specification steps involved in building such a system, along with the cost-savings benefited from the system.*
Keywords— *Condition-based maintenance, Fleet-management, M2M Telematics, Predictive Analytics*

I. Introduction

Approximately 30% of the life-cycle costs of a high-speed vehicle are spent on the maintenance of the vehicle, the largest spend besides energy [1]. The overall life-cycle cost distribution for a high-speed fleet is as shown below.



Pain-points that customers usually complain about such life-cycle costs are:
- Maintenance is the highest cost factor in the operations of high speed vehicles, besides energy and depreciation.
- Over a period of time, maintenance costs exceed the depreciation.
- Approximately 40% of the maintenance goes for the material / spare parts costs, while the remaining 60% amounts
to personnel costs.
- For an operational fleet, the depreciation and energy costs stay constant during the fleet's life-cycle, leaving the
maintenance cost as the only major cost position available for optimization [1][2].

- Thus, reducing the maintenance costs highly improves the profit margins for operators. The different maintenance
strategies followed by manufacturers and operators in this regard are as follows:

Corrective Maintenance: This is a Run-till-Failure methodology without any specific plan of maintenance in place.
Vehicle is considered to be functional and fit until it breaks-down.

Cons:
∟ Unexpected and uncontrolled production downtimes.
∟ Risk of secondary failures and collateral damage.
∟ Uncontrolled costs of spare parts and overtime labor.
Pros:
∟ Zero overhead of planning or condition monitoring costs.
∟ Machines are not over-maintained.

• **Preventive Maintenance**: A periodic maintenance strategy popular with the current manufacturers and vehicle service operators. Based on the asset design parameters, a potential breakdown period is pre-calculated and a schedule is pre-determined for preventive maintenance. Vehicle is subjected to regular maintenance periodically on those intervals,

irrespective of the usage pattern or the condition of the asset, assuming
that the vehicle is going to break-down otherwise.
o Cons:
∟A time-driven procedure. Assets are subjected to repair even in the absence of any faults.
∟ Unscheduled breakdowns can still happen
o Pros:
∟Maintenance cost estimates are known beforehand.
∟Inventory control and spare-parts planning is possible.
∟Fewer catastrophic failures and lesser collateral damage.

• **Predictive Maintenance (PdM):** This is an emerging strategy that applies predictive analytics to the real-time data gathered from the vehicles with the aim of detecting any deviations in the functional and behavioral parameters that can lead to vehicle breakdowns. Such anomaly detection procedures help identify the breakdowns as soon as their potential cause arises in real-time long before the break-down happens.

o Cons:
∟ Additional investment needed for the monitoring system
∟ Skilled labor specially trained to effectively use the system may be required.

o Pros:
∟ Parts are ordered on the need basis and maintenance is performed during convenient schedules.
∟ Unexpected breakdowns are eliminated.
∟ Reduced breakdowns result in maximum asset utilization.

Predictive maintenance, is also often commonly referred to as the Condition-based Maintenance (CBM), as it avoids the unnecessary inspection and repair costs by recommending a maintenance schedule that is based on the prevailing conditions of the machine in the real-world operating conditions [3].

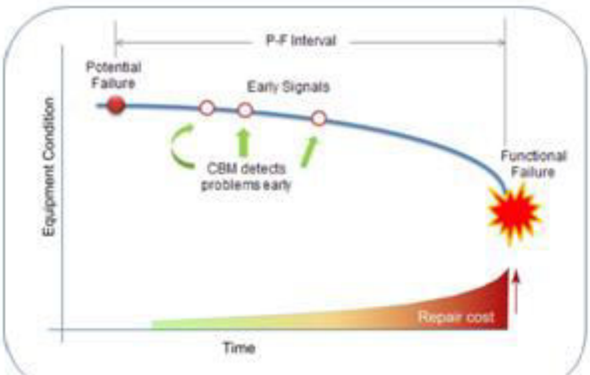


Figure 2. Predictive Maintenance reduces costs by detecting failures in early stages

To understand this, let us consider a typical periodic maintenance scenario for a vehicle. In a normal periodic maintenance mode, the vehicle owners are expected to change the engine-oil frequently at regular periods, such as after every 4 or 5 thousand Kilometers traveled. In such cases, the real condition of the vehicle or the performance capabilities of the engine-oil are not taken into consideration. Maintenance is carried out purely because it is as per the schedule. Had the owner had a way to realize the underlying vehicle condition (the remaining useful life, RUL), or the engine oil lubrication contamination levels at that instance, he or she could potentially either postpone the oil change, to a later point where the change is really needed, or even pre-pone it as per the prevailing conditions. CBM provides such capability to gain insight into the actual operating conditions of the vehicle and use them to accurately predict the maintenance requirements. Our earlier paper [3] presented an in-depth review on the inner workings of CBM systems and how in conjunction with sensor arrays and telematics they facilitate predictive maintenance.

Increased component availability, better worker safety and improved asset usage etc. are some of the compelling reasons why more and more operators and manufacturers are actively embracing CBM based fleet management solutions.

- Benefits for workers:
  - Work-life balance with predictable schedules
  - Turn-key solutions with zero paper work
  - Increased on-road safety
  - Navigation helpers and landmark guides
- Benefits for Management:
  - Reduced maintenance costs with Predictive Maintenance
  - Increased asset usage with zero unplanned downtime
  - Operational costs are reduced and idle times are eliminated with smart scheduling
  - Improved customer loyalty with always on-time deliveries
  - Theft and misuse prevention with real-time asset tracking

In the following sections, we present the methodology involved in designing such a condition-based maintenance management system using the machine-to-machine (M2M) approach, and showcase the architectural outline for one of our recently built system, along with the open-source tools and frameworks used in building the system and the cost-savings reported by the customers using it.

II. M2m Approach To The Cbm

A Condition-based Maintenance Management (CBMM) solution designed around M2M operates on three major technology directives:

1. Remote Sensor Monitoring & Data Capturing.
2. Real-time Stream Processing of Sensor Data.
3. Predictive Analytics.

Sensors are attached to the remote assets to collect various data about the assets' operating behavior and send it in real-time to a centralized monitoring station. The data arrives as continuous streams at the monitoring station, and is subjected to analysis using anomaly detection mathematical models to identify patterns of deviations in the expected functionality. Once any such anomaly is identified by the algorithms, owners are immediately notified indicating the potential failure and suggesting the appropriate corrective action. Handling such anomalies in timely manner prevents further functional degradation of the vehicle, thus avoiding potential costly breakdowns down the line. Often times the centralized monitoring station resides on the same network as that of the sensors (such as control area network) or it could be in a distant remote location connected through satellite networks or WAN.

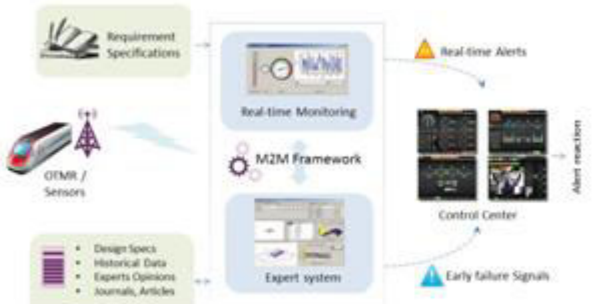


Figure 3. M2M facilitates real-time failure detection and prediction

During their operations, devices such as On-Train Monitoring Recorder (OTMR) for trains and Flight Data Recorder for flights record events in real-time from their connected vehicles, and either store them on-board for later processing when they reach their destination, or relay the events to the centralized processing system in real-time enroute using the machine-to- machine (M2M) telematics procedures and get processed on the fly to detect any current anomalies and predict future failures [4]. Nature of some of the data collected and analyzed for this purpose could be as follows:

- On-board Diagnostics (OBD) data: Vehicle speed, RPM, fuel etc.
- Driving Patterns: Acceleration patterns, braking patterns etc.
- GPS data: Locations, routing, length of stay of vehicle etc.

OTMR data: Door close status, Air suspension pressure, Brake dragging, HVAC failure etc.

In a nutshell, the concept of CBM is centered around: detect failures in their early stages so that you can prevent them from happening in the later stages. At the minimal level one can expect the below listed functionality from a well-designed CBMM system [7][8][9]:

- Find the Remaining Useful Life of assets
- Estimate the Failure Rate for assets
- Design a Predictive Maintenance Schedule
- Maintain right levels of Inventory for spare parts
- Schedule right skilled and sized workforce
- Optimize Inspection routines
- Decide right Warranty period at design time
- Evaluate What If alternate scenarios
- Compare different designs for reliability evaluation

A major challenge in implementing a CBMM system for high-speed fleet, however, is: processing the enormous volumes of data streamed-in from sensors attached to the high-speed vehicle in real-time. This requires:

- Parallel architectures capable of handling large volumes of data,
- Low payload data-structures that optimize sensor data bandwidth,
- Fault-tolerance capabilities that can deal with packet drops and fragile networks for real-time data streaming,
- Adaptable ontologies capable of supporting varied data types and protocols in parallel,
- Proof based security to ensure data privacy and anonymity.

Latest advancements in the Big-data open-source family of technologies offer viable solutions for the above requirements [5][6]. However, before one can design such big-data solution for the CBMM, the design process has to go through the requirement gathering and specification mapping stages to be able to accurately capture the customer requirements and realize them in software. The following section elaborates on this.

III. The Cbmm System Design Process

The design process starts with requirement gathering, which can be classified as addressing the three solution enabler stages as indicated below:

- Stage 1: Sensor data capturing stage
- Stage 2: Real-time stream processing stage
- Stage 3: Predictive failure-detection stage

The requirement gathering for stage 1 encompasses collecting information from the customer on the requirements of data capturing and real-time monitoring. Some of the questions that help gathering information from the customers at this stage are:

- What data should be collected and which sensors should be used?

E.g. thermal imagery, audio signals, etc.

- What are the components and parts that need monitoring? E.g. Engine Oil, Train brakes, Engine Crank Time, etc.
- How frequently the data should be collected? Hourly, daily etc.
- How to identify and handle faulty sensors?

In the requirement gathering for stage 2, the focus is on real-time processing of the collected data and some of the questions that customers need to answer in this stage are:

- What is the expected data processing latency?
- What should happen to the collected data post processing?
- How to address missing data points and inaccuracies? For example, a faulty sensor sending incorrect data.

For the final stage, the emphasis is on the analytical-subsystem. Customer requirements for this stage are collected through questions such as:

- Define the acceptable behavior and define the anomaly.
- What are the response actions for each anomaly class?
- What is the maximum acceptable time lag after the detection of the anomaly, before the corresponding corrective action takes place?
- How to deal with multiple anomalies detected at the same time?

Once complete, the gathered requirements are then formulated into a system specification that gives a formal outline of what is the expected from the CBMM. E.g. for the stage 1 requirements, the specifications outline what should be the operational level notifications possible in case of network unreachability for the sensors during the data capturing stage.

Similarly, stage 2 requirement specifications formalize the data-processing functionality. The specifications for this stage result in a matrix like structure as shown in the below table, where each component that is being monitored is listed alongside the possible events it can generate and the criticality of each event, along with what action, if any, should be carried out by the ground/operating crew monitoring that event.

Component	Event	Source	Event Criticality	Control Center Alert	Event reaction
Door	Closed *after* the train started moving	Door side camera	Low	-	-
Break	Emergency break tripped	OTMR	Critical	SMS/Email/ Escalation Matrix	Check power supply, air pressure

For example, in the above, one can see the component door being monitored for the close event, with a low criticality being attributed to it, while an emergency brake event is being monitored with high criticality attribution. Also, in case of emergency brake event, the event reactions list possible course of action, such as checking the power supply and air-brake pressure, which act as resolution guidelines for the crew and/or automated resolution solver system.

The specifications for the final stage revolve around failure prediction. Formal guidelines are established as to how a failure should be predicted and which data source and event should be used in the process. For example, the below table lists trend analysis criteria and pattern matching criteria as the stipulated methods for the door and break failure respectively.

Component	Event	Failure Indication
Door	Closed *after* the train started moving	1. Delay increasing, or 2. Happening for the last *n* observations (n > threshold)
Break	Abnormal break pressure patterns	Pattern matches with historical failure data

Based on these specifications, the CBMM system collects the data at the specified intervals from the sensors and utilizes the below methodologies to assert the asset's condition:

- Critical range and limits: Various statistical tests are performed to assert if the captured sensor data falls inside a critical failure range decided by the expert and requirement specifications [10].
- Trend Analysis: Verify if the vehicle condition is in a deteriorating mode with an immediate downwards trend towards breakdown [11].
- Pattern recognition: Establishes the causal relations between the events and the vehicle breakdowns [12].
- Statistical process analysis: Historical failure record data, collected through case-study histories, warranty claims and data archives, is processed with statistical procedures to find a suitable analytical model for the failure curves. As new data is gathered from the sensors, it is compared against those statistical models to predict the future breakdowns [13].

Trend analysis and critical range limit violations can be detected with real- time monitoring and stream processing of data. However, the pattern recognition and statistical process analysis requires historical data to be analyzed and compared against the real-time live data for insights. Usually such historical data is gathered through warranty-claims and maintenance records.

Advancements in the Big-data technologies and predictive analytics are enabling the stream processing of high volume live-data in real-time and matching it with the voluminous historical data offline. A referencarchitecture that was created for one of our large high-speed fleet management clients using the afore-mentioned design methodology on Big- data using M2M is as shown below:

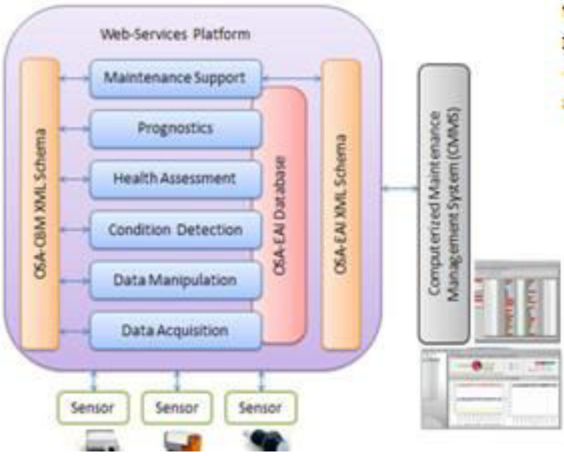


Figure 4. Reference architecture for condition-based maintenance mgmt. system

The layered architecture enables one to easily customize or upgrade only particular part of the system without completely replacing the whole system. The XML schemas used as the base to store and operate on the operating design specifications allow cross-platform compatibility and open-systems interoperability. Sensors communicate with the data acquisition and manipulation layers using the M2M framework, while the condition-detection, prognosis and health-assessment layers were implemented using Big-data parallelism. The maintenance support layers take care of the required notifications for the administrators and operating crew using the report dashboards and HMI visualizations along with security restrictions.
To achieve this level of sophistication, we integrated and customized multiple open-source frameworks to our requirements, some of which are listed below.

- Remote sensor monitoring & data capturing: OpenXc
- Real-time stream processing: Storm, Kestrel, ZMQ, MQTT
- Predictive analytics: R
- Real-time anomaly detection: Esper, CEP
- Distributed fault-tolerant storage: Hadoop, HBase
- Failure report dashboards: HTML 5
- Control center visualization: OpenGl, Vtk, Qt, HMI

The value-add in integrating and customizing these frameworks lies in achieving the required level of functionality with commodity hardware, enabling it to handle large volumes of data with adaptable ontologies all the while reducing the sensor data bandwidth. In their native form, individually, these open-source frameworks will not be able to achieve the afore- mentioned objectives in a manner suitable for enterprise customers [14]. The integration and interconnection of different technologies used for implementing this solution is as shown below:

Figure 5. Technology stack integration for our condition-based maintenance management solution

After the initiation of a fully functional CBMM system, our customer reports have indicated the following year-wise average savings resulted across their business units:

- Reduction in maintenance costs: 25% to 30%
- Spare parts inventories reduced: 20% to 30%
- Reduction in equipment downtime: 35% to 45%
- Elimination of breakdowns: 70% to 75%

- Overtime expenses reduced: 20% to 50%
- Asset life increased: 20% to 40%
- Increase in production: 20% to 25%

While the predictive technology reduced the unexpected brake-downs, the collateral benefits, such as work-life balance (with no unexpected brake- down calls), reduction of over-time expenses and improved asset availability contributed to the production increase rates.

IV. Conclusion

Advancement in the big-data technologies in combination with M2M and predictive analytics is creating new possibilities for real-time analysis of machine components for detecting failures in the early stages and avoiding them ahead of time. Increased component availability, improved worker and environment safety, better asset usage etc. are some of the reasons that are attracting more operators and manufacturers to embrace condition-based maintenance strategy in their operations. Designing such a system for high- speed fleet, however, requires special attention to the design methodologies used for collecting the operating requirements from the users and translating them into big-data parallel architectures that are capable of exhibiting fault-tolerant behavior and load-balancing possibilities to sustain the real-time data processing demands. This paper presented reference architecture for one of our big-data M2M systems we designed as a large fleet-management solution for a customer and showcased the technology framework interconnects used in the said system. With more and more customers becoming interested in these solutions, one can expect more solutions built on these architectures using the listed frameworks and suggested design methodologies in the future.

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