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IntelligentLogger: A Heavy-Duty Vehicles Fleet Management System Based on IoT and Smart Prediction Techniques

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***Abstract*—**Both daily and long-term management of a heavy-duty vehicles and construction machinery fleet is an extremely complicated and hard to solve issue. This is mainly due to the diversity of the fleet vehicles – machinery, which concerns not only the vehicle types, but also their age/efficiency, as well as the fleet volume, which is often of the order of hundreds or even thousands of vehicles/machineries. In the present paper we present "InteligentLogger", a holistic heavy-duty fleet management system covering a wide range of diverse fleet vehicles. This is based on specifically designed hardware and software for the automated vehicle health status and operational cost monitoring, for smart maintenance. InteligentLogger is characterized by high adaptability that permits to be tailored to practically any heavy-duty vehicle/machinery (of different technologies -modern or legacy- and of dissimilar uses). Contrary to conventional logistic systems, which are characterized by raised operational costs and often errors, InteligentLogger provides a cost-effective and reliable integrated solution for the e-management and e-maintenance of the fleet members. The InteligentLogger system offers the following unique features that guarantee successful heavy-duty vehicles/machineries fleet management: (a) Recording and storage of operating data of motorized construction machinery, in a reliable way and in real time, using specifically designed Internet of Things (IoT) sensor nodes that communicate through the available network infrastructures, e.g., 3G/LTE; (b) Use on any machine, regardless of its age, in a universal way; (c) Flexibility and complete customization both in terms of data collection, integration with 3rd party systems, as well as in terms of processing and drawing conclusions; (d) Validation, error reporting & correction, as well as update of the system's database; (e) Artificial intelligence (AI) software, for processing information in real time, identifying out-of-normal behavior and generating alerts; (f) A MicroStrategy based enterprise BI, for modeling information and producing reports, dashboards, and alerts focusing on vehicles–machinery optimal usage, as well as maintenance and scraping policies; (g) Modular structure that allows low implementation costs in the basic fully functional version, but offers scalability without requiring a complete system upgrade.

***Keywords*—**E-maintenance, predictive maintenance, IoT sensor nodes, cost optimization, artificial intelligence, heavy-duty vehicles.

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I. Introduction

E-MAINTENANCE is a relatively new concept that started appearing in the literature in the early 2000's and since then has become a frequently found term in the literature dealing with contemporary maintenance developments [1]. Although e-maintenance is a still evolving multidisciplinary field, for which different definitions have been suggested [2], [3], a general definition could be that it is a "maintenance management concept whereby assets are monitored and managed over the Internet" [2]. In any case, e- maintenance is currently considered to be in line with Industry 4.0, exploiting the synergy of computer, electrical and mechanical engineering for the efficient and effective management of assets [4], [5]. E-maintenance relies on the collection of big data collected in real time from a multitude of sensors installed on the assets, as well as to warehouse information and their utilization for the development of intelligent decision-making algorithms that can drive the efficient management of assets. Of course, IoT sensors are of outmost importance in designing a successful smart logistics system [6].

A particularly demanding case of e-maintenance is the day-to-day and long-term management of an inhomogeneous fleet of construction machinery and heavy-duty vehicles, of very different types, technologies, age, etc., which are operated under different environmental operating conditions, by operators of different experience/dexterity, etc. Towards addressing this complicated e-maintenance case, we propose the "InteligentLogger" system, which offers an expandable, reliable and low-cost solution that incorporates several unique characteristics. InteligentLogger builds upon a custom design of a versatile IoT sensor node for the real time collection of vehicle/machinery-related data, as well as on advanced data handling and AI models for the identification of irregular operation, and finally business intelligence (BI) models for report, dashboard and alerts production.

The rest of the paper is organized as follows: Section II analyzes the challenges of a heavy-duty vehicles fleet management; Section III presents the proposed solution.

II. Challenges of Heavy-Duty Vehicles Fleet Management

Construction companies use a variety of specialized equipment of different types and capacities. Size of such fleets may vary from a few hundred up to many thousands of

machineries. Management of equipment fleet is an everyday challenge for the construction companies, with significant impact to their results, in terms or profitability, quality assurance and safety.

Fleet management's purpose is to ensure that adequate types and quantity of machinery will be available for the execution of projects' works, on time and in a cost-effective way. Fleet management involves an extended, very complicated and different in nature number of actions, that involves:

i. Good prediction of machinery fleet requirements.
ii. Optimal strategy for the fleet assembly.
iii. Cost prediction in short term (running cost/maintenance), but also in long term, e.g., how productive and cost efficiency is a machine as it gets older with respect of a new one.

More precisely, the actions required during the planning and executing of a new project are:

a. Determining type, specifications and number of equipment required for each task.
b. Indicating equipment source (purchase new, hire/lease, utilize equipment already existing in fleet, or subcontract).
c. Defining maintenance schedules for each machinery.
d. Organizing service stations for executing equipment scheduled maintenance as well as unpredicted repairs by own means (mandatory, especially for projects located in remote areas).
e. Establishing partnerships with 3rd parties for the execution of equipment maintenance and repairs.
f. Ensuring supply of parts, consumables and materials required for equipment operation and maintenance/repair, and the existence of specialized personnel.
g. Ensuring compliance with international and local lows, project and client requirements, safety and environmental rules and restrictions and issuing of the required documents (certificates, licenses, etc.).
h. Monitoring of equipment actual utilization and recording of operational data (operating hours, fuel & lube consumption, etc.).
i. Recording actual equipment cost per type and size of equipment:

- Owning cost (depreciation, cost-of-money).
- Running cost (fuel & lubricants, consumables, materials, tires, repair labor cost, insurance, work permits, surveys, certificates, etc.).

j. Controlling compliance with the schedules, identifying deviations in terms of time or cost and applying corrective actions.

Furthermore, accurate recording and prediction of running cost of a machinery fleet is one of the fundamental aspects that a construction company has to take into consideration, as it allows to:

a. Evaluate equipment costing rates (e.g., cost/time unit) to correctly estimate the equipment cost for future projects (overpricing reduces competitiveness, while underpricing reduces profit margins).
b. Estimate equipment budget cost of running projects to manage project's cash flow.
c. Identify deviations from projects budget cost and react promptly.
d. Make decisions regarding the acquisition method of equipment (e.g., purchase or hire).
e. Estimate equipment useful life and determine owned equipment depreciation and replacement policy.
f. Identify equipment that is no more cost-effective and reject or replace them.

As it is clearly understandable, the correct and timely (with real time being the optimum case) collection and evaluation of equipment operational information (location, operating status, fuel and lube consumption, engine rpm, engine oil temperature, etc.) are key aspects of a fleet management system, as they allow to:

a. Improve the existing preventive maintenance schedule by implementing condition-based maintenance which leads to fewer unscheduled repairs, less break down time and increased equipment availability. Consequently, the ratio of total equipment cost per time unit will be improved.
b. Check the appropriate usage of the equipment and place warnings/provide instructions to the responsible construction foremen and machinery operators.
c. Identify hazardous situations and initiate alarms.

The everyday collection of the above required equipment information, the registry of the data into databases and the subsequently post-processing to generate the reports required for supporting fleet management decisions are very complicated and bureaucratic processes. This process involves different kind of highly specialized software and applications, including Enterprise Resource Planning (ERP), Fleet Management System (FMS) or asset management software, pricing software, business intelligent tools, time-keeping systems, fuel/lube recording systems, Central Processor Unit (CPU) reader, vehicle diagnostic software etc., as well as consuming enormous amounts of labor-hours and involving risks of non-accurate data or error inputs due to the extended engagement of manual actions. Most of these tools are specialized to fit to specific equipment types, are not compatible or difficult to connect to each other, and require highly educated staff. To overcome this highly bureaucratic complexity there is a need of a holistic system that:

1) is flexible and highly parametrized in terms of:
a) collections methods. The system should be:
i) compatible to all construction equipment (regardless of their age, technological evolution, manufacturer and type) and collecting in real time the needful information directly from the equipment (timestamp, geographical position, operational status, engine data, other system data, etc.).
ii) ready to receive other equipment information such as financial information (depreciation, etc.), repairs and maintenance information (labor hours, labor cost, spare part cost, consumables, etc.).
b) processing information and drawing conclusions.
2) performs validation check and presents faults and corrections registry.

3) is equipped with a smart, user friendly software for the information processing and real time or long-term reporting (reports, dashboards, statistics, predictions, proposals), that can be tailored to each user needs.

III. Description of the Suggested Solution

The proposed solution, "IntelligentLogger", aims at consolidating information from different sources in a data warehouse and using it to provide both corporate and worksites with the required insights for heavy equipment. The block/logical diagram of IntelligentLogger is shown in Fig. 1. As there is a major issue regarding quality and availability of data, we introduce a specially developed IoT sensor node in each equipment to acquire real time information directly from the machine. This device can acquire information from built-in sensors, external configured sensors and on-board diagnostics (OBD) data from the equipment where it is installed, in a flexible and compatible way, regardless the type and the age of the machine. After the device's installation and configuration, it is registered to a cloud service termed 'Sensor Consolidation Service' (SCS) (see Fig. 1) and then starts to upload the recorded data in a reliable way in real time.

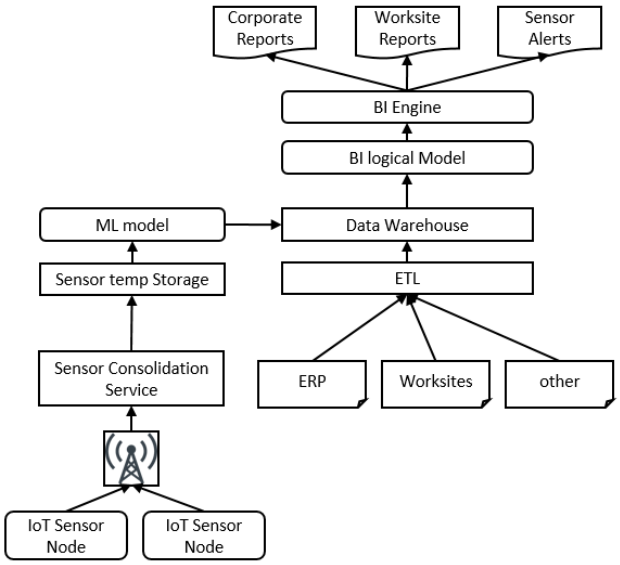

Fig. 1 Block/Logical diagram of IntelligentLogger components

In cases that the real time uploading is not possible (e.g., lack of infrastructure networks at the worksite), we introduce a specific android application (that can run on any android tablet or smartphone). In such cases the android application acts as intermediate between the cloud and the IoT sensor node, by downloading the data on worksite from the machines and uploading them later to the cloud, when a network is available. Furthermore, the android application can be used to register data which are not possible to be automatically recorded (e.g., fuels, lubricants, spare parts replacement etc.) and upload them in a universal way, overcoming bureaucratic processes of high complexity.

The information that SCS collects from each IoT sensor node is: device ID, timestamp, longitude, latitude and up to 8 analog and 3 digital sensors readings, corresponding to the sensor channels that are available on each device. Common sensor readings are engine speed (rpm) and engine temperature (ºC), but depending on the individual equipment configuration, devices can also output vehicle speed (km/hr), battery voltage, hydraulic pressure, coolant pressure and temperature, fuel level and consumption, OBD fault alarms and more.

TABLE I
Corresponding IoT Sensor Node to Equipment

Equipment Code	IoT Device ID
Equipment Code 1	IoT Sensor Node ID 1
Equipment Code 2	IoT Sensor Node ID 2
Equipment Code 3	IoT Sensor Node ID 3
…	…
Equipment Code m	IoT Sensor Node ID n

TABLE II
Sensor Type Connected to Each IoT Sensor Node's channels

IoT Sensor Node ID	Channel 1	Channel 2	Channel 3	Channel 4	…
IoT Sensor Node ID 1	Sensor ID 1	Sensor ID 2	Sensor ID 3	Sensor ID 4	…
IoT Sensor Node ID 2	Sensor ID ...	Sensor ID ...	Sensor ID ...	Sensor ID ...	…
IoT Sensor Node ID 3	Sensor ID ...	Sensor ID ...	Sensor ID ...	Sensor ID ...	…
…	…	…	…	…	…
IoT Sensor Node ID n	Sensor ID ...	Sensor ID ...	Sensor ID ...	Sensor ID ...	…

TABLE III
Sensors' Characteristics and Conversion Function

Sensor ID	Physical quantity	Unit	Conversion function
Sensor ID 1	Engine Oil Temp	ºC	$y = 0.00000001*x^2 + 0.00571906*x -38.64534272$
Sensor ID 2	Coolant pressure	PSI	y = 0.005*x + 15.001
…	…	…	…d
Sensor ID n	…	…	…

SCS gathers information from the IoT sensor nodes installed on the equipment and performs basic filtering and transformations. More specifically, SCS links the information collected by the devices to specific equipment using a matrix that corresponds device ID to the equipment Code to which the device is currently installed on as in Table I. SCS identifies sensor type by using a matrix of the form of Table II indicating the sensor type connected to each channel of every device. Then SCS calibrates sensor readings to physical values, using the adequate conversion function for each sensor type as shown in Table III. SCS filters out invalid records and measurements and outputs equipment information and its operating data (Equipment ID, timestamp, longitude, latitude, and operating data from the sensors).

Data from the SCS are gathered in a staging environment where they are processed to the machine learning (ML) model for fault detection. Also, they are feed to a geofencing algorithm to identify cases of theft or inappropriate use. All

results from both systems are feed to the data warehouse (DWH).

In the DWH, all information for the different sources is gathered, cleaned, normalized and consolidated. One characteristic in this situation is that there is significant variance in frequency, reliability and information grain between different systems. The main sources that are used are the company's ERP holding mainly financial and approved operational information which is available in irregular intervals a few times a year. The granularity for this information is monthly. A second source is data from worksites, with monthly frequency and daily granularity. There are both financial and operational data from worksites, but also information about maintenance and repairs. Finally, there are other data sources, like inventory information on equipment, project, and worksite related information etc.

In the DWH information is maintained in a snowflake schema, using the "most reliable source" for each piece of information and granularity. Aggregated daily sensor measurements are considered most reliable. Second in preference come workshop data and finally the monthly grain of ERP. Using aggregated information provides the added benefit of being able to provide insights that previously took months to be available much more sooner.

The DWH is used as a data source to the BI suite which is using the MicroStrategy platform [7]. There are two main layers to this implementation, one logical, where all data in the DWH are mapped to the respective business entities and the reporting layer, where the actual reports, dashboards and hyperintelligent cards are available to the users.

User access to the reports and rights to view data is managed by the platform. Users are divided according to their function and need for information consumption to two major groups: Corporate and Workshop. Corporate requires primarily information in monthly level while Workshop mainly deals with daily data.

For the implementation of the SCS, a serverless architecture has been designed using the Microsoft Azure public cloud provider. The architecture is presented in Fig. 2. Azure provides out-of-the-box resources that can handle massive amounts of IoT data and execute event-triggered functions that are able to transform and transmit the messages.

The messages received by the IoT sensor nodes are ingested via Azure Event Hubs. Azure Event Hubs is a real time data ingestion service that can handle millions of events per second and can be scaled according to the data input volume [8]. After receiving the message, the Event Hub triggers the execution of an Azure Function that will process it.

An Azure Function is a serverless block of code that can be executed as a response to a trigger [9]. The message is being processed and all necessary transformations are being executed within the context of the function (e.g., the linking of the message to a specific equipment). If no errors are found during the execution of the function, the processed message is being transmitted onto the staging environment. If an error is found, the messaged is stored onto a log table and an informative email is being sent to a recipient list.

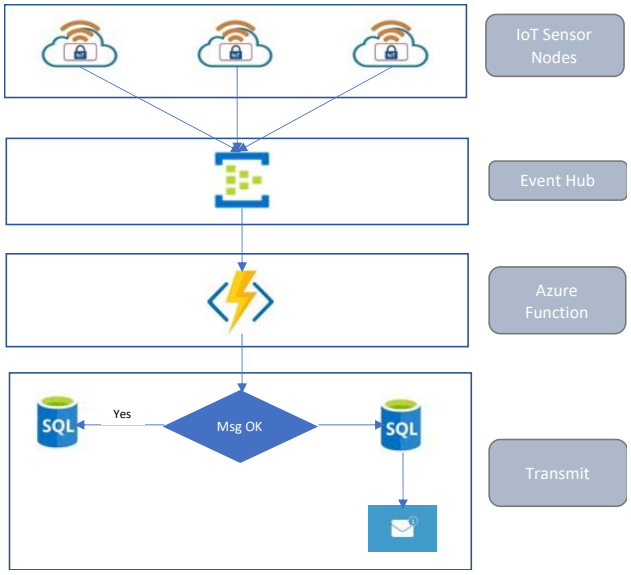

Fig. 2 Logical diagram of SCS

The DWH is implemented based on the Kimball architecture [10]. An Extract Load Transform (ETL) stage is used to gather, clean, and normalize data from various sources. A delta mechanism is used to identify new and updated records, and maintain changes to the slowly changing dimensions of the DWH - Types 0, 1 and 2 are implemented. Deletions are received as updated records flagged as deleted. Validations include type and value checks, as well as referential integrity validations. Only a temporary stage level exists to assist in the ETL process and data are stored directly to fact and dimension tables.

In the case that the direct communication from the IoT sensor nodes to Event Hub is not possible (e.g., lack of infrastructure networks in the worksite), the specially developed android application is used as the intermediate uploading mechanism, keeping all the logs and machines ID as in the case in the real time uploading. The same scheme is followed for the entries that are not possible to be automatically recorded by the IoT sensor nodes (e.g., fuels, lubricants, spare parts replacement etc.), keeping also in this case the ID association to machine's ID for universal handling of data.

The DHW is implemented in a snowflake schema, as this is preferable for the MicroStrategy platform [11], especially since aggregate tables are used in this implementation (there are two grain levels in different fact tables, day and month). To support further expansions, it was decided to store more information than what is necessary for the current reporting needs, so as to maintain historical information for future development. Besides the data coming from the company's systems, sensor data are also maintained, both as aggregations (daily and monthly) and as the results of the ML and geofencing algorithms.

The system will maintain a 40-year history for information in monthly grain and a two-year history for daily data, to be able to provide detailed comparison reports vs previous year.

In Fig. 3 all the business processes mapped in the DWH with the associated conformed common dimensions. In this DWH Bus [11], the main focus of all processes is equipment information, as it is used by different departments. In this implementation, emphasis is placed in the maintenance and repair of equipment, both from a financial point of view and in terms of operations. It is worth mentioning the "Normalized Calendar" dimension, which is necessary to provide a common time dimension for comparing equipment data from different calendar periods. Normalized Calendar calculates the months since purchase of each equipment, providing a common time dimension for evaluating cost factors of different equipment. Most of these dimensions represent hierarchies. And there are some minor dimensions as well that represent specific equipment characteristics like condition and usage.

Business process	Calendar	Normalized Calendar	Equipment Classiciations	Combined Equipment	Geography	Manufacturer	Employees
Workshop Optimization	X		X	X	X		X
Equipment Maintenance	X	X	X	X	X	X	X
Preemtive Maintenance	X		X	X	X		
Equipment Monitoring (opex)	X	X	X	X	X	X	
Equipment Distribution	X		X		X	X	
Purchase/sell/rend Equipment	X	X	X	X	X	X	
Worksite Financial Managemen	X		X		X		
Supplier Evalutaion	X		X		X	X	
Project Management	X		X		X		

Common Dimensions

Fig. 3 DWH Bus Architecture for common dimensions

The reporting produced is divided to two main categories: those intended for corporate use and those for worksites. Corporate reports are primarily monthly reports, providing an overview of the usage and cost of the equipment in various worksites. Utilization, cost breakdown, cost-effective evaluation, repair costs and equipment depreciation, owned vs rented equipment are the major issues that are covered in these reports. One of the major concerns that this implementation addresses is the question of when an equipment has passed its usefulness, and it is no longer cost-effective to maintain it.

Reports for worksites can be monthly or daily and are more operational in nature. Equipment monitoring, status and utilization are presented for workshops. Alerts indicating preemptive maintenance are generated from IoT data and others from geo-fencing can be used for theft prevention. There are also detailed reports on workshops and the repair/ maintenance work carried out, in order for managers to smooth workload and optimize resource utilization. Time and cost are the main factors in these reports.

Alerts are generated by a ML algorithm developed for identifying faults in the monitored equipment. So far, two types of common faults have been trained: Coolant fluid leakage and engine oil filter failure. The main difficulty in training these models was the availability of adequate data with these faults. In the current implementation, we used a small number of actual data 2 incidents per fault and then with the assistance of experts from the construction company, simulated 40 time series of samples per fault in order to train and test the models.

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