Integrated Prescriptive Maintenance System (PREMSYS) for Construction Equipment Based on Productivity

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Abstract. It is now imperative to create smart systems that prevent mechanical damage through timely preventive maintenance, particularly in construction projects with strict time schedules and budgets. Construction equipment is the largest capital investment for construction companies. Proper maintenance is of major importance for efficiency, productivity, minimization of equipment costs, and environmental management. The aim of this study is to propose an integrated smart system that will monitor the condition based on productivity of the equipment and will provide diagnostic data, helping to optimize the production process, achieve timely maintenance and increasing the expected "economic" life of the equipment. At the same time, it will positively provide the concept for sustainable or green construction with the minimization and elimination of harmful effects on the environment and on the human. The system will include sensors, placed on specific construction equipment components, and will collect measurements for their use and condition, through real-time data export. These data will then be sent using wireless networks to a main server. Extraction of performance measurements and machine learning (ML) data processing will determine when the equipment needs predictive maintenance and repair. Proper, timely and prescriptive maintenance of construction equipment will reduce their environmental footprint and any human harmful emissions, while saving energy during their operating phase and optimizing production processes through monitoring “dead” time.

1. Introduction
This study aims to cover the need for timely and accurate prediction for construction equipment maintenance and productivity monitoring, in large and costly projects. In the European Union, it is a common practice to execute most of the public works through co-founded financial projects. Those projects are characterized by tight budgets and strict timetables. Therefore, it is imperative for the project managers to adopt a coherent strategy for reducing the total cost and the project’s completion time, to eliminate any financial problems during its execution. Additionally, current construction industry faces an imbalance between the vast amount of data, extracted originally by the equipment, and the lack of appropriate domain structures for storing, filtering, processing and exploiting the above data.

The main goal of this study is to propose an integrated smart system, able to constantly monitor the real time condition and productivity of the equipment. This system will provide real time diagnostic data, contributing to the equipment’s profitability optimization, through timely maintenance and
increase its economic life expectancy. At the same time, it will contribute to the adaptation of a sustainable or “green” environment.

The successful completion and implementation of the proposed system will provide prescriptive guidance to the equipment owners regarding the most efficient type of maintenance needed, while it will offer constant awareness about the equipment’s economic life. Namely, it will recognize if the equipment is still profitable or not, and needs to be replaced. The smart system will be trained by three types of data: a. historical equipment’s data, regarding its operability and maintenance, gathered from the equipment owners, b. equipment’s standard data, provided by the Original Equipment Manufacturers (OEMs) preinstalled sensors and indicators, and c. data coming from the sensors installed on specific equipment’s parts or components, in order to collect additional data from their current use. Those specially designed sensors will collect and analyze those data in real time, into a central server (cloud or standard), transmitted through a chosen type of wireless network. The data transmission will be done in certain forms, allowing much faster and efficient processing.

Fundamental subject of this study is to develop targeted industrial research actions for monitoring, rendering, analyzing and evaluating the most significant factors affecting the equipment’s efficiency. At the same time, environmental polluting factors (gas emissions, noise pollution) will be restricted, with beneficial effects also for the equipment’s operators (less vibrations, increased safety through constant monitoring and timely treatment of potential failures).

The proposed system includes nine scientific and technological challenges: a. Design, development and installation of a prototype life-cycle management system and its comparative evaluation to demonstrate its proof of concept, b. Comprehensive approach of the equipment’s efficiency and behavior, through real-time status recording by specially designed sensors and data transmission through modern wireless networks, c. Classification and ranking of the observed equipment’s metrics for each type of equipment, d. Development and installation of specially designed sensors, where their proper operation and adequacy will be scientifically documented, e. Design and development of smart systems able to provide guidance for operational decision-making regarding the equipment’s maintenance and strategic decision-making for the holistic approach regarding the equipment’s efficiency, behavior and economic life, f. Feed the smart system and its subsystems with real-time collected data, followed by their constant improvement and comparative evaluation through Machine Learning models, able to monitor the equipment’s current status, by simultaneously knowing their operational and maintenance history, g. Investigate the commercial utilization of the final product or some of its parts, by developing a comprehensive business plan, in order to quantify its business oriented results, and h. Construction equipment market investigation about the application of fleet management software, in order to integrate the results of this study to their functionality. The last-mentioned investigation has been completed and its results are presented in CCC 2021.

The innovation of this study is based on the development of a coherent, multi-parametric approach, for the optimization of a comprehensive construction equipment management. Predictive maintenance, productivity and operational analysis of construction equipment will be integrated into a smart information system, giving constant real-time results. The use of sensors, with IoT capabilities will provide scalable abilities to the initial system infrastructure with low cost.

2. Literature Review
Marinelli and Lambropoulos (2012) investigated the cost implications that the earth loading and hauling trade-off involves for an earthmoving fleet and introduced a method for the selection of the most expedient loading practice.

Alshibani and Moselhi (2012) presented a newly developed optimization simulation model for fleet selection for earthmoving operations. Global positioning system (GPS) data was used to build and update in near real time the developed model. The model is designed to assist contractors in selecting equipment fleet configurations for earthmoving operations; taking into consideration: (1) uncertainties associated with a set of quantitative variables that represent loading, hauling, and dumping duration, as
well as project direct and indirect cost; (2) availability of resources to contractors; (3) project cost and (or) time constraints; (4) project indirect cost; and (5) scope of work.

Marinelli and Lambropoulos (2013) managed to optimize scraper’s load-time by applying an algorithmic method that incorporated the golden section search and the bisection algorithm.

Memarzadeh et. al. (2013) presented a computer vision-based algorithm for automated 2D detection of construction workers and equipment from site video streams. Their research proposed semi-automated detection methods for tracking of construction workers and equipment. Unlike other state-of-the-art algorithms in automated resource tracking, their method particularly detected idle resources and did not needed manual or semi-automated initialization of the resource locations in 2D video frames.

Aziz et. al. (2014) developed a model which incorporates the basic concepts of Critical Path Method “CPM” with a multi-objective Genetic Algorithm “GA” simultaneously. This model suggested a practical support for compound horizontally and vertically mega construction planners who needed to optimize resource utilization in order to minimize project duration and its cost with maximizing its quality simultaneously.

Marinelli et. al. (2014) presented an artificial neural network (ANN) model that predicts earthmoving trucks condition level using simple predictors; the model’s performance is compared to the respective predictive accuracy of the statistical method of discriminant analysis (DA). Their data processing identified a particularly strong connection of kilometers travelled and maintenance level with the earthmoving trucks condition level. Moreover, the validation process revealed that the predictive efficiency of the proposed ANN model was very high. Similar findings emerged from the application of DA to the same data set using the same predictors.

Said et. al. (2014) developed a novel telematics-based computational methodology to support two major equipment fleet management tasks: fleet use assessment and equipment health monitoring.

Yip et. al. (2014) presented a comparative study on the applications of general regression neural network (GRNN) models and conventional Box–Jenkins time series models to predict the maintenance cost of construction equipment. Both GRNN and Box–Jenkins time series models described the behaviour and predicted the maintenance costs of different equipment categories and fleets with an acceptable level of accuracy. Forecasting with multivariate GRNN models was improved significantly after incorporating parallel fuel consumption data as an explanatory time series.

Heidari and Marr (2015) employed a portable emission measurement system (PEMS) for real-time measurement of carbon dioxide (CO2), nitrogen oxides (NOx), hydrocarbon, and carbon monoxide (CO) emissions from construction equipment to derive emission rates (mass of pollutant emitted per unit time) and emission factors (mass of pollutant emitted per unit volume of fuel consumed) under real-world operating conditions.

Kim et. al. (2016) presented an on-site safety-assessment system for monitoring struck by accidents with moving entities based on computer vision and fuzzy inference. Next, fuzzy inference was used to assess the proper safety levels of each entity using spatial information. The proposed system provided valuable information regarding worker safety represented as a numerical value.

Naskoudakis and Petroutsatou (2016) conducted a meta-analysis of the latest journal papers dedicated to construction machinery, in order to systematically review research themes related with optimization, maintenance/downtime, productivity, robotics and automation, operator’s competence, innovation and environment. In the second part of their review, they provided useful pointers regarding the optimum selection of fleet equipment as a key factor for the success of any construction project.

Vanraj et. al. (2016) presented a state-of-the-art review of various Condition Monitoring methods and signal processing techniques used for the Predictive Maintenance of mechanical systems. Conclusively, vibration analysis has proven to be an important criterion for fault diagnosis in manufacturing processes and maintenance scheduling for various manufacturing equipment.

Azar (2017) presented an automated system to analyse the content of heavy-construction videos, including videos with moving viewpoints, and to index them based on midlevel (i.e., objects) and high-level (i.e., operations) semantic content.
Burgler et. al. (2017) presented a method for estimating the productivity of soil removal by combining two technologies based on computer vision: photogrammetry and video analysis. The automated generation of progress and activity statistics from both measurement methods supported interpretation of the productivity estimates. Comparison to annotated ground truth for the tracking and activity monitoring method highlighted the reliability of the extracted information.

Hamledari et. al. (2017) presented a computer vision-based algorithm that automatically detects the components of an interior partition and infers its current state using 2D digital images. The method's high accuracy rates, its fast performance, and applicability to different contexts such as automated robotic inspection are indicative of its promising performance.

Holt and Edwards (2017) conducted a numeric, theoretical analysis using the Caterpillar® hydraulic excavator productivity model to estimate excavator production, given: first, variance in modifying factors based on derived maximum and minimum values; and second, variance resulting from linear calculations based on excavator operator competence. Their findings dictated that excavator productivity resulting from incremental variance of modifying factors in isolation is shown to be linear except, in the case of bucket payload.

Park et. al. (2017) presented the Stochastic Dozer Productivity Estimation (SDPE) method, which integrates dozer production estimating curves and equipment specification obtained from manufacturers, defines the probability density functions (PDFs) of job condition correction factors, executes the dozer productivity estimating format (DPEF) for the user-defined number of iterations, and estimates the best-fit PDFs of productivity and that of total owning and operating (O&O) cost.

In order to strengthen the supervision of construction workers to avoid accidents, Fang et. al. (2018) proposed the use of a high precision, high speed and widely applicable faster Region Based Convolutional Neural Networks (R-CNN) method to detect construction workers' NHU, with data collected from far-field surveillance videos of different construction sites.

Gwak et. al (2018) presented a computational method called Optimal cut-fill Pairing and Sequencing (OPS), which identified the most economical earth allocation planning (EAP). They identified the optimal cut-fill pairs and their sequence which minimizes the total earthwork cost by hybridizing the mixed integer linear programming (MILP) and evolutionary algorithm.

Kim et. al. (2018) investigated the feasibility of measuring machinery cycle times by using inertial measurement units (IMUs) embedded in a smartphone. To enhance the recognition of the equipment’s mixed activities and translate the results into reliable cycle time measurements, a dynamic time warping (DTW) algorithm was applied and the DTW distances of IMU signals were used as additional features in activity classification.

Lee et. al. (2018) developed a GPS only-based fleet telematics system for heavy earthwork equipment which could analyse time log information of each equipment using GPS location data without utilizing any other on-board sensors and CAN bus data. Algorithms to analyse the utilization time of earthwork equipment using GPS location information was designed and their reliability was verified through field tests.

Petroutsatou and Marinelli (2018) published their book about the operational analysis of construction equipment and highlighted the necessity of predictive maintenance and proper equipment management when coming to enhance their productivity.

Kim et. al. (2019) presented a non-intrusive earthmoving productivity analysis method using imaging and simulation, to analyse jobsite contexts and the necessity of a complex multi-camera surveillance system or workers' privacy issues. An algorithm for license plate detection and recognition in an uncontrolled environment was developed to automatically produce the site access log, by leveraging video deinterlacing, a deep convolutional network, and rule-based postprocessing. Based on the site access log, simulation-based productivity analysis was conducted to produce a daily productivity report, which can provide the basis for earthmoving resource planning.

Kisi et. al. (2019) proposed a two-prong strategy for estimating optimal labour productivity by quantifying systematic and operational inefficiencies. In that way, they confirmed the feasibility of applying this approach to complex operations involving multiple workers or sequential and/or parallel
tasks and actions. Their study augmented the two-prong strategy’s methodology to apply the approach to a complex, multi-worker operation necessitating both sequential and parallel tasks and actions.

Petroutsatou and Giannoulis (2020) analysed the Greek construction equipment market sales and its consumers from 2000 to 2015 and identified the factors that affect a machine’s value and the most important equipment characteristics. This analysis determined the equipment to be used to develop the proposed integrated system of this research.

3. Theoretical foundation and concept development
This paper proposes a conceptual model for the holistic integration of four major research components: a. Construction equipment life cycle management system development, b. Development of sub-systems of data information and their integration into a smart system concerning the equipment’s life cycle management, c. Development, installation, and pilot operation of sensors, and d. Pilot operation and system evaluation.

3.1. Construction Equipment Life Cycle Management System

3.1.1 Literature review and market research
In this stage, a scientometric analysis will take place, to investigate the scientific and the enterprises interest on the research, with the use of VOSViewer and RapidMiner Studio software. It will ensure the adequacy of the collected data, on factors related to construction equipment’s workload. A structured questionnaire has already been disseminated among construction equipment OEMs, owners, practitioners and other experts, to identify the type, frequency and weight of importance for the most common construction equipment’s failures and damages, during their operation. Six types of equipment will be used: a. Dozers, b. Graders, c. Front Loaders, d. Backhoe Loaders, e. Excavators, and f. Dump Tracks. The evaluators were asked for each type of failure: a. To report the frequency of each failure that occurs yearly, b. How serious and how risky is each failure, regarding productivity, downtime and safety, and c. The type and number of sensors needed to constantly measure certain indicators, to avoid each failure. The questionnaire results are summarized in Table 1. F stands for Flow, H for Humidity, L for Length, P for Pressure, S for Sound, Tem for Temperature, Ten for Tension and V for Vibration.

| S/N | Equipment Type | Failure Type | Failure Frequency (occurrence/year) | Average interval time between failures (months) | Failure weight (scale 1-3) | Failure Risk (scale 1-3) | Number of Required Sensors | Type of Measurement |
|-----|----------------|--------------|-------------------------------------|-----------------------------------------------|---------------------------|--------------------------|--------------------------|---------------------|
| 1   | Dozer          | Filter - Gas Pump | 2 | 6 | 3 | 1 | 1 | 1 | F |
| 2   | Gearbox        |              | 1 | 12 | 3 | 3 | 2 | 2 | V, S |
| 3   | Main Front Blade Hydraulic System x Axis Pistons Oil Leak | 3 | 4 | 2 | 2 | 3 | L, P, H |
| 4   | Main Front Blade Hydraulic System y Axis Oil Leak | 3 | 4 | 2 | 2 | 3 | L, P, H |
| 5   | Main Front Blade Wear | 3 | 4 | 3 | 1 | 1 | 1 | L |
| 6   | Crawler Tension Mechanism (spring) | 3 | 4 | 1 | 2 | 1 | 1 | Ten |
| 7   | Fuel Consumption & Working Hours | 0.4 | 30 | 3 | 3 | 2 | 2 | P, Tem |
|     | TOTAL          |              |                            |                                             |                           |                           |             |         |
| 1   | Grader         | Main Leveling Blade Wear | 3 | 4 | 3 | 1 | 1 | 1 | L |
| 2   |                | Main Leveling Blade Rotating System Stabilizers Wear | 1 | 12 | 3 | 3 | 1 | 1 | V |
| 3   |                | Main Leveling Blade Mounting System Hydraulic Lifting Pistons Oil Leak | 2 | 6 | 2 | 2 | 3 | L, P, H |
| 4   |                | Gearbox      | 1 | 12 | 3 | 3 | 2 | 2 | V, S |
| 5   |                | Filter - Gas Pump | 2 | 6 | 3 | 1 | 1 | 1 | F |
| 6   |                | Tire Replacement | 0.4 | 30 | 3 | 3 | 2 | 2 | P, Tem |
| 7   |                | Fuel Consumption & Working Hours | 1+1 | OEM | 12 |   |   |   |         |

Table 1. Most Common Construction Equipment Failures.
### 3.1.2 Data Collection, Evaluation and Life Cycle Management Database Development

In this stage, historical operating and maintenance data is collected and evaluated. The data concerns each equipment’s operating and maintenance logbooks; these records are being kept by the equipment owners or users. For the purpose of this research, those records will be categorized, classified and verified accordingly, in order to form a homogeneous database. Specialized metrics will be extracted, regarding operational equipment’s trends, equipment operators’ behaviour, failure frequencies, equipment’s downtime, maintenance strategy and policy application, etc.

### 3.1.3 Collection and Evaluation of the Sensor’s Data

The measurements being derived from the sensors, installed on specific equipment’s components and parts, will supplement the above “historical” database, to test the existing machine learning model and to lead to more accurate results.

### 3.2. Informational Sub-System Development - Integration to a Smart Equipment’s Life Cycle Management System

#### 3.2.1. Mathematical Modelling for Predicting the Equipment’s “Economic Life” and Decision-Making Modelling

At this stage, an artificial intelligence integrated system will be developed for predicting the equipment’s “economic life”, by providing instructions for a new form of guided maintenance and decision making (prescriptive maintenance). This smart system will be the integration result of two sub-systems. The first

| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | TOTAL |
|---|---|---|---|---|---|---|---|---|-------|
| 1 | Wheeled Backhoe Loader | Front Bucket Hydraulic Lifting Pistons Oil Leak | 2 | 6 | 2 | 2 | 3 | L, P, H | 20 |
| 2 |  | Front bucket hydraulic pistons oil leak | 2 | 6 | 2 | 2 | 3 | L, P, H |  |
| 3 |  | Boom arm hydraulic pistons oil leak | 2 | 6 | 2 | 2 | 3 | L, P, H |  |
| 4 |  | Backhoe hydraulic pistons oil leak | 2 | 6 | 2 | 2 | 3 | L, P, H |  |
| 5 |  | Gearbox | 1 | 12 | 3 | 2 | 2 | V, S |  |
| 6 |  | Filter - Gas Pump | 3 | 4 | 3 | 1 | 1 | F |  |
| 7 |  | Front/rear bucket teeth ware | 3 | 4 | 1 | 1 | 1 | L |  |
| 8 |  | Tire Replacement | 0.4 | 30 | 2 | 3 | 2 | P, Tem |  |
| 9 |  | Fuel Consumption & Working Hours | +1 | OEM |  |  |  |  |  |
| 1 | Wheeled or Crawled Excavator | Bucket Teeth Ware | 3 | 4 | 1 | 1 | 1 | L |  |
| 2 |  | Boom Arm Hydraulic Pistons Oil Leak | 2 | 6 | 2 | 2 | 3 | L, P, H |  |
| 3 |  | Bucket Hydraulic Piston Oil Leak | 2 | 6 | 2 | 2 | 3 | L, P, H |  |
| 4 |  | Filter - Hydraulic Oil Pump | 3 | 4 | 3 | 1 | 1 | F |  |
| 5 |  | Filter - Gas Pump | 3 | 4 | 3 | 1 | 1 | F |  |
| 6 |  | Tire Replacement | 0.4 | 30 | 1 | 2 | 2 | P, Tem |  |
| 7 |  | Crawler Tension Mechanism (spring) | 3 | 4 | 1 | 2 | 1 | Ten |  |
| 8 |  | Fuel Consumption & Working Hours | +1 | OEM |  |  |  |  |  |
| 1 | Wheeled Crawler Loader | Gearbox | 1 | 1 year | 3 | 3 | 2 | V, S | 14 |
| 2 |  | Bucket arm hydraulic lifting pistons oil leak | 3 | 4 months | 2 | 2 | 3 | L, P, H |  |
| 3 |  | Bucket hydraulic pistons oil leak | 3 | 4 months | 2 | 2 | 3 | L, P, H |  |
| 4 |  | Bucket Teeth Ware | 3 | 4 months | 1 | 1 | 1 | L |  |
| 5 |  | Filter - Gas Pump | 3 | 4 months | 3 | 1 | 1 | F |  |
| 6 |  | Tire Replacement | 0.4 | 2.5 years | 2 | 3 | 2 | P, Tem |  |
| 7 |  | Fuel Consumption & Working Hours | +1 | OEM |  |  |  |  |  |
| 1 | Dump Truck | Gearbox | 1 | 1 year | 2 | V, S |  |
| 2 |  | Dumper lifting pistons oil leak | 3 | 4 months | 3 | L, P, H |  |
| 3 |  | Wheel Suspension piston leak/ware | 0.5 | 2 years | 3 | L, P, H |  |
| 4 |  | Wheel Suspension Spring tension ware | 0.5 | 2 years | 1 | Ten |  |
| 5 |  | Filter - Gas Pump | 3 | 4 months | 1 | F |  |
| 6 |  | Filter - Hydraulic Oil Pump | 3 | 4 months | 1 | F |  |
| 7 |  | Tire Replacement | 0.4 | 2.5 years | 2 | P, Tem |  |
| 8 |  | Fuel Consumption & Working Hours | +1 | OEM |  |  |  |  |  |
| 1 | Dump Truck | TOTAL | 14 |  |  |  |  |  |  |

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one will accept the historical data information, while the second will analyse the data coming from the specifically installed sensors on certain equipment’s parts or components, which are recording in real time the equipment’s condition and efficiency on the field.

3.2.2. Development of the Software’s Final Version
After the completion of the pilot equipment’s operation and the system’s evaluation, the final version of the management software will follow.

3.3. Construction, Installation, and Pilot Operation of Sensors

3.3.1. Sensors Construction
Those specially constructed sensors will utilize the most developed communication networks, to transfer the collected raw data into the main database. Those networks will allow the sensors to communicate with the project’s base stations under severe electromagnetic conditions, such as being next to the equipment’s motor engine, inside underground constructions or in distant and inaccessible working areas. The sensors will include three main components: a. The sensing elements, integrated into the electronic circuit, to transform the physical measurements into manageable electronic data, b. A special extremely low-energy microcontroller, which will receive the data from the main processing unit in real time, and c. The communication component, able to transmit great amount of data.

3.3.2. Installation and Pilot Operation
The sensors will be placed on specific equipment’s parts or components. During this pilot phase the sensors will be charged directly from the equipment’s battery. The aim is to record the necessary physical measurements (e.g. temperature, vibrations, pressures, fluid flow), which will constitute a rich database, sufficient to feed the smart system and train it.

3.4. Pilot Operation and System Evaluation

3.4.1. Pilot Operation Design
The selection of the main operating elements of the system, which will constitute the pilot’s system testing elements, is crucial for the overall design of the evaluation process. This process also includes the operational design for the sensors installation and the system’s implementation, to be able to operate in real-time. In addition, expedient interfaces will be developed, to monitor the pilot system operability.

3.4.2. Pilot Operation and System Evaluation
Finally, a pilot operation of the final smart integrated system will be performed. The sensors will receive their final set up and they will be tested, evaluated and their final structure will be decided. A comparative performance evaluation will be performed, by comparing the results from the equipment’s field testing with the experimental results.

4. Expected Outcomes
This study proposes clear research and operational goals, the fulfillment of which will lead to the following achievements: a. Database development for six types of construction equipment (For the Greek market, the analysis made by Petroutsatou and Giannoulis (2020), identifies that the most used and popular equipment are Crawler/Wheeled Excavator, Wheel Loader and Wheeled Backhoe Excavator), by combining the historical operation, maintenance and failure data with the data coming from the OEM’s pre-installed sensors, b. The construction of specially designed sensors, used for the constant measurement of several values, i.e. temperatures, vibrations, pressures, fluid flow etc., which will be able to utilize the most recently developed communication networks, to feed the database with data, and c. The development of a smart system, based on machine learning techniques, able to manage
the processed data and propose solutions for the equipment’s maintenance and its further use (Explainable Artificial Intelligence). Figure 1 depicts the above approach.

Figure 1. Research’s Concept Development

5. Conclusion
This study contributes to the current body of knowledge in construction equipment and management by demonstrating a conceptual model for the development of an integrated smart system for monitoring the real-time status and productivity of six construction equipment types. It will contribute to the real-time collection of diagnostic data, regarding the type of maintenance needed, and it will decide if the equipment is still profitable or not, or it needs to be replaced. The achievement of the above goals will determine the final creation of the decision-making tool, which will allow, on the one hand timely prognosis and failures repairs, while on the other hand it will decide whether the equipment’s operation and ownership is still financially efficient. Additionally, by utilizing Machine Learning methods, the proposed model will be able to demonstrate accurate predictions on several equipment’s productivity indicators. Determining the feasibility of this methodology in a complex environment is the first step towards building a future tool that will apply to field practitioners, construction companies, repair companies, dealers and OEMs.

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