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The Big Role of Data Analytics in the Industrial Internet of Things

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Abstract*: An IoT architecture is presented in the article which is a predictive way to maintain a group of buses using J1939 sensor data[1]. The authors adopted a minimally viable prototype (MVP) at the Socie´te´ de Transport de l'Outaouais (STO) garage in Gatineau, Canada, which was able to capture around 1 GB of uncompressed J1939 data per bus every day.[1] Data is a combination of the sensor reading and consists of data for the wheel speed, vehicle distance, driver pedal positions, engine information, oil information, coolant information, and transmission fluid information. The authors are trying to come up with a variant of Consensus Self-Organized Models (COSMO) named ICOSMO, which can self-fit the sensor selection for anomaly detection.*

The fourth industrial revolution has changed the face of ancient manufacturing by bringing in new technologies such as sensors, AI, IoT, and big data analytics. This equipment is used to convert factories into intelligent and interconnected systems that generate a huge amount of data. The data collected, when properly processed, can be utilized to improve decision making and reliability and safety. In addition, it makes predictive maintenance inevitable, thus minimizing the downtime and optimization of the performance[2]. Industrial big data is identified by the "5V" elements: volume, velocity, variety, veracity, and value. Due to these characteristics, traditional data processing techniques become inadequate, so these circumstances require novel approaches to the treatment of the numerous and diverse data types that are produced in industry 4.0.

The Proposed ICOSMO Infrastructure for IoT Predictive Maintenance consists of the following key activities: 1) finding out which sensor classes are the reasons for the faulty components, 2) adaptation of the sensor class (SC) and the sensor prediction capability (SPC) using fault detection abilities and 3) COSMO sensor configuration has to be rearranged after a certain period of time. ICOSMO has been verified with data from a minimally viable prototype (MVP) deployed on buses at the Socie´te´ de Transport de l'Outaouais in Canada. Furthermore, the interviewees said that the framework also includes techniques for the composition and the characterization of industrial big data, which is essential to make a practical predictive maintenance system that can work in smart manufacturing environments

Keywords: ICOSMO

I. INTRODUCTION

The IoT architecture is the topic of the article that provides a solution to predictive maintenance for a fleet of buses using the J1939 sensor data. The authors implemented a minimum viable prototype (MVP) in Gatineau, Canada, at the Socie´te´ de Transport de l'Outaouais (STO) garage and it gathers nearly 1GByte of J1939 compressed data per bus everyday.[1] This data includes sensor readings such as the wheel speed, vehicle distance, driver pedal positions, engine information, oil information, coolant information, and transmission fluid information. Entering the paper by the

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researchers, they discussed the updated version of the Consensus self-organized models (COSMO) approach, named ICOSMO, which makes sensor selection for anomaly detection change automatically.

RehumanizeIndustry 4.0 presents a complete evolution of the way manufacturing in traditional industries is now to become. It is through the utilization of advanced sensor systems, AI, the IoT, and big data analytics that these factories are able to attain digitized operations. This data captured can, if properly analyzed and processed, become a resource to enhance decision-making, thus making it possible to achieve increase in reliability and safety, and contributing to energy usage efficiency by performing predicative maintenance that will reduce downtimes and increase productivity

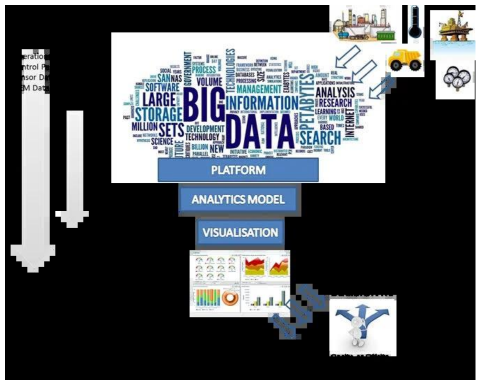

Fig. 1. BDA in IOT

Redefining-the way of looking at the industrial data- cognitively, the ”5V” attributes: volume, velocity, variety, veracity, and value are the fulcrum. The emergence of these features creates difficulties, which in turn, means that existing data processing methods are challenged to the limit. Therefore, the Industry 4.0 regime demands new approaches and paradigms that will accommodate inter alia, diverse and vast data issuing from facilities in the digital environment.

Three essential stages of predictive maintenance framework for the Internet of Things (IoT) systems have to be followed for the implementation of the ICOSMO model. These stages include identifying sensor classifications related to the known faulty elements, adjusting the sensor class and sensor prediction capability (on their fault detection level), and eventually restructuring the COSMO sensors chosen one time in a while. ICOSMO was double-checked through the use of data from a minimal viable prototype (MVP) placed on buses at the Socie´te´ de Transport de l’Outaouais in Canada. The model also involves new techniques for structuring and getting rid of and characterization industrial big data which is important in enabling predictive maintenance in smart manufacturing environments.

II. PREDICTIVE MAINTENANCE WITH BIG DATA ANALYTIC

A nice piece of technology is presented in a paper - the so-called IoT architecture for predictive maintenance for a collection of buses by means of J1939 sensor data. the J1939 sensor data. The authors introduced at the launch - and a prototype as a result - a minimally viable product (MVP) at the Socie´te´ qui des Transports de l’Outaouais (STO) garage located in Gatineau, Canada, which was able to get 1 GB of uncompressed J1939 data on a daily basis from a single bus. The mentioned data also provided speed of one or both wheels, travelling distance, and the location of the driver’s pedal all along with the engine information, oil information, coolant information, and transmission fluid information which were included.

Authors suggest an upgraded Consensus self-organized model (COSMO) method, called ICOSMO which adapts sen-sor selection for abnormal incident recognition with time in a dynamic way. ICOSMO assumes the presence of a bus sensor maintenance database, VSRDB, with repair records that correspond to the malfunction, a document retrieval method to identify classes of sensors used with fault components, and that all buses in the fleet are from the same model with similar daily travel routes. The MVP hardware setup is a Raspberry Pi, a UPS, a GSM module, a Wi-Fi antenna, a power converter, and on a J1939 electronic control unit (ECU) installed in a waterproof container on a

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bus. Software integrates with MeshCentrals for network administrators and is stored on a laptop for the STO garage J1939. The authors want to increase the MVP panel by including more buses through gateways as well as complete the ICOSMO for predictive maintenance research.[01]

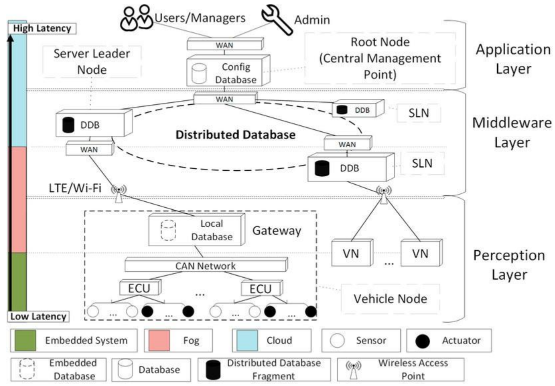

Fig. 2. Predictive maintenance fleet management system architecture- overview diagram[01]

A novel IoT architecture for predictive maintenance is the main subject of this work and it proposes a semi-supervised machine learning algorithm to enhance the sensor selection in the COSMO system. In a data-driven context, ICOSMO is purposed to run predictive maintenance with the help of the most common sensor data from different periods. According to a data-driven approach, ICOSMO is primarily engaged in predictive maintenance since mainly the latest and past sensor data are available.

ICOSMO is the exclusive way of detecting high frequencies. It is divided into two branches: THE first is the BBDRA which starts with the process of finding the sensor classes that are involved with the faulty component. The next is SC and SPC which are sensor instances that can be modified using the calculated indicator values of their abilities (or potential abilities) to detect deviations. The other section is to detect this sensor array is ASCR problem of geometric organization if the majority of the sensor class sensor instances can be found by the other sensor arrays. Deletes or adds sensor classes to COSMO's selection based on the overview of the parameters of the majority of the sensor instances of each

new sensor class picked by the COSMO's decision maker. The production will involve running simulations and modeling to create data by means of the STO J1939 data dumps derived from the MVP. Experiments involving different flavors of COSMO will be carried out to compare the performance of ICOMSO to a number of COSMOs.[01]

RehumanizeTo test ICOSMO, simulations and modeling will be performed by generating data using the MVP information in its STO J1939 data dumps. The experiments will be conducted to compare the ICOSMO performance with the noozle. [01]

Structuring

The conversion of unstructured and semi-structured data into the structured format is the initial step. In the case of semi-structured data like XML, semantic web technology is the tool used. Unstructured data like video will be manipulated to create a structured model through the process of noise elimination and feature extraction.

Rehumanize Characterization

Characterizing industrial data in the big data realm must include characteristics that are not only related to time but also to space and time as well. Proper defining should be carried out through the following:

Spatial Feature: Exploring and identifying the discrete re- mote modules of a factory in a manufacturing process.

Time Feature: Various sensors keep an eye on industrial[02] Rehumanize Case Study

The suggested structure has been confirmed by performing the case study where we predicted the remaining useful life of the main parts of the CNC machining center by using multiple source data that are different from one another. Vibration signals, 3D laser scanner images, and power data are analyzed to predict tool wear and performance. The

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research proves to a great extent that taking into account multiple sources of data for prediction ultimately leads to more accurate and robust solutions in comparison with relying on single-source data.[02]

Rehumanize Complex System Health Management in Indus- try 4.0: Leveraging Big Data for Predictive Maintenance

Rehumanize Introduction to Industrial Big Data in Industry 4.0

The fourth industrial revolution has brought changes to the traditional manufacturing industry through the use of advanced technologies like sensors, AI, IoT, and big data analytics. Factories are converted by these technologies into smart, interconnected systems that are smart and can generate large amounts of data. This data, when properly processed, can enhance decision-making, improve reliability and safety, and enable predictive maintenance to minimize downtime and optimize performance.[02]

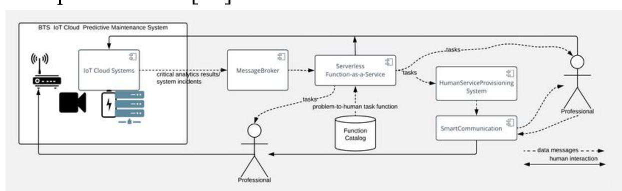

Fig. 3. BTS, data sources and services for predictive maintenance[03]

Key Properties and Difficulties of Industrial Big Data[02] By establishing predictive maintenance in Internet of Things cloud systems, this paper presents a combination of human responsibilities with functionless servers. It discusses the process to use with RAHYMS and other Human Service Provisioning Systems (HSPS) to allocate work to experts based on the incident complexity and the specialists' proficiency. To pass the necessary information on to the responsible workers, a communication module is utilized together with a rule creation mechanism that links events to services and professions. The concept is illustrated with the instance of a system that undertakes integration of human activities like data transmission, and also the HVAC issue (such as uncontrolled cooling).Complex maintenance operations that need the use of both digital analytics and the power of human intellect to get done, the ability to set up rules for machines, make use of the latest HSPS, and provide intermediary to human software specialists is very important.[03]

For announcement of error situations and delivery of re- quired analytical data to digital interfaces, we depend on messaging techniques. Due to functions, that are void of the need for servers, companies can use services to send messages not only to human customers but also to machines and programs in the Internet of things or in the cloud and connect to big data without any intermediary.

Less perplexity which pointing out that the message doesn't include basic terms and common expressions accepted by AI like ChatGPT.[03]

III. PROCESS OPTIMIZATION THROUGH BIG DATA ANALYTICS

The digitalization of manufacturing introduces an ecosystem of technologies in sensing, connectivity, data modeling, and decision-making .[10] Sensors collect real-time data from machinery and processes, enabling predictive maintenance and quality control. Connectivity technologies, such as IoT and industrial Ethernet, ensure seamless communication between devices and systems, enhancing automation and efficiency. Data modeling creates representations of relationships between data points, facilitating accurate analysis and insights. Ad- vanced decision-making tools, often powered by AI and ma- chine learning, utilize this data to optimize operations, improve productivity, and drive innovation, transforming traditional manufacturing into a more intelligent and responsive industry.

Hui Guo et al. [33][34] came up with an open network framework for the Internet of Things that allowed for separate IoT apps running in different environments. The infrastructure helps to connect to the internet many multiple IoT devices and real systems in an interoperability-isolated way: black boxes are applied for many layers of the underground stack of communication, hardware, and software. It is thus a model of transparency that uses systems underpinning different plat- forms which are difficult to visualize. IoT deployments are now even more agile due to the tactics of virtual physical devices on cloud networks and allowing inter and intra ap- plications to communicate, scale and work effectively. As a result, it not only is a cost-efficient approach but also is a way to optimize the

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resources, system efficiency, and general performance, thus it is a crucial milestone in IoT infrastructure and application development.

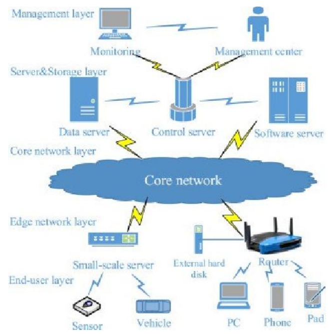

Fig. 4. A scalable architecture for IoT based on transparent computing[33][34]

The problem of scalability and sustainability of IoT devices is addressed by cloud technology [15]. IoT systems can grow along with increasing data and device connections, as they are engineered to take advantage of the cloud. Thus, the costs of initial investment can be reduced if the infrastructure scales up or down based on demand. Further, cloud computing solutions provide strong, always-on support thereby, increasing the permanency and reliability of IoT devices. It is this capac- ity of converting computational ability, storage and network resources that makes it possible to manage IoT systems more efficiently.

IV. DATA SECURITY AND PROCTION IN BIG DATA ANALYSIS

The course of events that are yet to come in this universe are trumped by ML driven IoT paradigms (Internet of Things) that project to make mater things smart with artificially received intelligene [21]. By means of combining ML algorithms with IoT devices, these paradigms empower things to learn from data, look up information, and execute decisions. As a result of this, simple objects are converted into smart devices capable of complex functionalities such as predictive maintenance, personalized user experiences and automated control systems. It goes without saying that the implementation of ML in IoT would bring about more interconnections leading to a smart environment which would, in turn, result in important points of innovation and efficiency in medicine, commerce, and smart cities.

Different privacy has been investigated by Wu et al. where they explained a problem using the term of owners of private data. This they achieved by introducing blur to interdependent values of private data [16]. The way it works here is that each individual's record/data is always, one way or another, confi- dential, and at the same time, one nobody can say anything about them is not true of the aggregate data. This includes noise in a non-destructive way, which in effect masks the private information that could be disclosed from the database and so reduces the user's privacy. One approach that is capable of achieving this level of security is by enabling this channel with controlled noise. This method can be widely used in the field of data security and by the government in systems related to health insurance, banking, etc. Without a doubt, it can be the solution that makes personal data be secure at the same time letting valuable insights and analytics be discovered.

The study mentioned in [27] is mostly about the use of big data analytics to diminish botnet attacks which occur almost everywhere. Employing data science techniques such as phasedaranalysis scam detection, trustedcookie-based risk prevention, and smartcaptchas response to these swarming bot activities is perceived. Because of the information derived from figures and facts such as, "network traffic patterns, anomalies, and behavior", "bigger datasets enable earlier de- tection" is the main focus of the research. Increasing the effectiveness of methods of defending against the botnet phenomenon is the aim of the project that deals with the study data collected in a 24-month-long period. Utilization of big data in a preventive manner, instead of being reactive is a good strategy for companies as they can make the security posture of big data analytics use them to secure solutions from potential risks caused by social engineering techniques, unnatural behavior of man-in-the-middle attack victims, and their interaction with gadgets and e-governments details.

V. ACKNOWLEDGMENT

'Volume, velocity, variety, veracity, and value' are the char- acteristics of industrial big data that normal data processing tools like traditional techniques find tough to handle, for which new techniques are required in order to deal with the data, diverse, and volume of the data generated by an Industry 4.0 environment[2]. The directed framework that (comes with) data structuralization, multi-scale characterization, and model- ing of invisible factors, does it by improving the transparency, and the ability to do preventive maintenance in the manufac- turing systems[2]. Structuralization needs the conversion of the unstructured and semi-structured data into a structured format/ It uses the structuralization of the geometry, which allows the extraction of spatial and non-linear features, to extract structural patterns from 3D geometry and characterize structures of a material with specific defects. The examples provided within the framework confirm the efficiency of the model by forecasting the main elements of a CNC machining center that are in their current stage; in this case, it is the use of multisource heterogeneous data to make the prediction, which in turn shows that the results of such forecasting are more accurate and steady when data from various sources is employed, i.e., multisource, as opposed to using a single source.

VI. SUMMARY

The ICOSMO predictive maintenance framework proposed in the IoT system contains three main points of the process: Request ICOSMO was already validated with the prototype installed on buses in Canada and it proposed a time frame for deploying my solution at Metro in Hungary. identifying sensor classes connected to deficit components the sensors of the sensor class, known in the literature [](SC) and sensor prediction capability (SPC) will be modified according to their fault detection capability, and 3) periodical regrouping of the selected COSMO sensors. ICOSMO was verified and validated by using data from a minimally viable prototype (MVP), which was operated on buses at the Socie´te´ de Transport de L'Outaouais in Canada. The framework also has tools for structuring and characterizing industrial big data that are crucial for accurate predictive maintenance in smart manufacturing environments .[1][2]

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