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MMS Predictive Maintenance Big Data Analytics

MD. Rakibul Islam Ratul

B. Tech, Department of Aeronautical Engineering, Jain (Deemed-to-be University), Bengaluru, India

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ABSTRACT

Maintenance avoids manufacturing issues. Maintain. Predictive maintenance is crucial since catastrophic component failure may affect performance and security. Big data predictive maintenance enhances visibility, speed, and accuracy. Simulate sensor-monitored semiconductor manufacturing plant maintenance decision support and Big Data maintenance policy framework. AI anticipates component failures—Predictive Maintenance. Maintenance prevents costly issues. This research uses service log-based data Centre predictive maintenance. Bologna INFN-CNAF data Centre employs reactive maintenance. Log data may enhance data Centre service. Logs may show system health. ML-supervised data analysis involves time and money. Environmental data may improve prediction and diagnosis. After an introductory discussion, this article explores how topics like Big Data, the internet web of things, predicting technology, and predictive analytics affect planned and predictive maintenance. Do repair shops earn? Simplifying. Smarter manufacturing 4.0. IoT devices create machine data. Statistics aid business choices. Data analytics 4.0 tackles large and small datasets. Today's competitive business requires companies to analyse massive data and generate new ideas quickly. Manages huge datasets. Hadoop runs Hadoop. Big data enables predictive maintenance. Big data forecasts public datasets—variable graphs Minimise Maintenance—machine component failure spectrum. Big data helps businesses.

Keywords: Data, datasets, analytics. Maintenance, component, manufacturing, machine, forecasting, semiconductor

1. Introduction

One area where the promise of big data is realised is in predictive maintenance, which has far-reaching consequences for how businesses function. Predictive maintenance uses data analysis to forecast potential system or mechanical problems, allowing for preventive steps. Predictive maintenance, enabled by big data, may improve output, save costs, and tighten security, all of which will be discussed in this seminar report.

During the last several years, there has been a surge of curiosity about the potential of big data applications in predictive maintenance. To better understand the condition of their machines and when they need servicing, many companies in the Industry 4.0 age rely on big data. Predictive maintenance aims to reduce the need for emergency repairs and subsequent costs. This seminar report will examine how leveraging big data to fuel predictive maintenance may benefit businesses.

Several disciplines make use of massive data sets. It has simplified the analysis of large datasets to make predictions. Predictive maintenance relies heavily on big data, which analyses past data to anticipate when machines may break down. The purpose of this research is to see whether as well as how big information might help with preventative upkeep.

What are the predictive maintenances?

Predictive maintenance can assess whether or not the equipment needs to be repaired and the optimal time to repair. Predictive maintenance aims to reduce the number of expensive failures and unforeseen costs associated with their repairs. Assessing data from various sources, such as machine sensors, maintenance records, and environmental data, is required to predict when maintenance will be required accurately.

The term "predictive maintenance" refers to analysing data to identify future issues before they occur in equipment. This approach deviates from the conventional practice, which entails doing maintenance at regular intervals or responding to problems as they manifest themselves. A process known as predictive maintenance aims to maximise the amount of time that equipment is operating while simultaneously lowering the amount of money spent on care and improving operational efficiency.

How is Big Data Used for Predictive Maintenance?

Predictions of when and why machinery will break down may be made using big data by analysing the data for recurring trends. To achieve this goal, businesses must compile information from various sources, such as equipment sensors, maintenance logs, and operational data. Machine learning algorithms are then used to use this data to draw conclusions and discover trends.

Having access to relevant data is crucial for effective predictive maintenance. Companies will need to spend money on sensors and data-gathering systems to ensure they get accurate readings. This also implies businesses need to put money into machine learning algorithms that can find trends and extrapolate information.

2. The importance of Predictive maintenance

Predictive maintenance is crucial for avoiding unscheduled downtime since it may foresee potential machine issues. Consequently, accidents and production losses may be reduced since repairs may be made before a failure causes damage or downtime. Organisations may get more use out of their machinery, extend its useful life, and reduce repair costs using predictive maintenance. Businesses that conduct their operations in potentially dangerous environments would invest in predictive maintenance as it can reduce the frequency of incidents and increase worker safety.

Using big data for predictive maintenance has the potential to provide many benefits. Firstly, it might help with budgeting for maintenance by predicting when machines would go down. This allows maintenance to be planned during off-hours when it will have the most negligible impact on productivity and operations.

Second, it might extend the time before the next unexpected piece of equipment breakdown, increasing availability. This is excellent news for companies since unplanned downtime may result in lost production time and cash.

To sum up, using big data for predictive maintenance aids in improving operational efficiency. With this information, organisations can better prepare for maintenance, which reduces unscheduled downtime and increases production.

3. Literature review

The burgeoning field of BD increasingly relies on data and the integration of information systems. Due to its dynamic nature, BD has attracted the interest of academics and professionals alike. This represents the pinnacle of cutting-edge business technology. "BD" has recently become trendy (Waller and Fawcett, 2013). It has also shown the value of BD in influencing company decisions and boosting productivity in Malaysia. Businesses, researchers, and the financial community have all taken notice of the "quantitative information explosion" caused by the actions of social media and Internet users. "Web 2.0" was coined by Roger Mouglas and initially used by O'Reilly Media in 2004. (Beebe, 2019).

When Mouglas first used the word "BD," he referred to reference datasets that were too large to manage with traditional BI software. The government sector may benefit much from BD, notably in cost reduction, service improvement, and occupancy insights. Using big data analytics to real estate data for predictive maintenance can inform policymakers, managers, and citizens about issues, including resource allocation, asset effectiveness, and potential threats or opportunities. Having everything in one place may assist in organising a portfolio with many sites, types of buildings, and gaps. It may not be easy to understand government real estate since so many facilities areowned and operated by one entity and used by several tenants. Choices on what to buy, sell, rent, or occupy might benefit from the additional information made available by a centralised data management system. Large amounts of data are collected from field operations to improve maintenance management. Inspectors may make predictions, such as the relationship between maintenance job needs and expected workforce increases or decreases. Maintenance management makes it possible to minimise the frequency with which preventive maintenance (PM) must be performed to minimise the associated costs. The purpose of maintenance management is to boost inspection intervals. There are two ways to avoid equipment breakdown: the first is to anticipate potential failure points, and the second is to take preventive measures like scheduling regular maintenance.

Data-driven Maintenance

Almost all sector of the economy is impacted by BD. Financial services, healthcare, education, retail, and government are just some sectors that stand to gain from this BD trend. Utility companies, those tasked with easing traffic, those charged with preventing crime, and many more may all benefit from the insights gleaned by BD analysis conducted by government organisations. The government's use of BD applications for asset and facility management may vary widely depending on factors including decision-maker preferences, information intake and output formats, quality, available data, and the approach used to derive business values. In contrast to popular belief, BD is not a standalone system but rather a method and the use of technology to achieve a goal. The media and telecom industries will be among the first to adopt BD fully. The government sector is expected to have the slowest adoption rate in the immediate future. Sixty percent of Western Europeans surveyed in the research by (Villars et al., 2011) were aware of BD but had no intentions to apply it in their businesses. Maybe the public sector is lagging behind others because of reservations about its use of BD. The four components of a BD technology architecture ensure that BD apps continue functioning as intended during scheduled upkeep: architecture, information management, analysis techniques, and applications.

(1) Infrastructure: This tier's servers, storage, and networking are examples of hardware.

(2) Data management:Software for managing and storing data, including Relational Database Management Systems (RDBMS), Non-Relational Data stores, including Hierarchical Databases and Graph Databases, and Structured Query Language (SQL) databases.

(3) Equipment for Analyses: The tools used to do this, as well as to watch and analyse the data, such as displays, visual data gathering tools, and internal business reporting instruments. There are also analytics like text mining and preventative maintenance analytics that help pull out necessary details (For instance, when analytics programmes provide computed scores or text analytic instruments measure mood)

(4) Importantly: Implementations like detecting fraud, inside which patterns, as well as suspicions of fraud, are equalled to transactions to predict fraud, and demand planning, in which a PM implementation anticipates future requirements using previous requirements as well as other relevant information, are the focus of this BD-enhanced layer.

The Government of Malaysia like any other governing body, the Government of Malaysia relies heavily on reliable information to make policy decisions. Since the amount, velocity, variety, validity, and value of data increase exponentially, decision-makers must have access to BD tools to help them extract actionable insights from this information. Maintenance management must combine data about a facility to carry out their duties and make essential choices. The problem is that maintenance managers don't always have access to the complete and coherent datasets they need to improve their decision-making. Mobley (2008) and Sullivan et al. (2005) show that responding to failures is both time-consuming and costly, effectively shortening the lifespan of facilities. (2010) since there is no accurate information to foresee failures or do preventive maintenance. This has implications for M&R procedures, particularly those used by governments to care for their assets and buildings. Information on maintenance and repair tasks performed by a maintenance department is often recorded on a work order (WO). Nevertheless, WO data is often isolated in silos (paper or computer records, i.e., CMMS)rather than being analysed with other facility data (Horizontal or vertical) area, a particular component, or a particular structure. Unfortunately, there is no connection between the data provider and the database. Maintenance managers must execute their studies ad hoc, with results restricted by the data available in each system. The management or technical team may determine whether there are issues with the building's equipment and facilities by comparing the component's performance history; Examining the feasibility of using groups of maintenance and repair workstations for visible performance evaluation.

4. The Importance of Big Data in Proactive Repair

Becausebig data's inherent capacity to collect and analyse large amounts of data from sensors, equipment, and other sources has become a vital resource for predictive maintenance, machine learning algorithms and different methodologies are applied to the data to predict future issues. With big data, companies may better predict when specific equipment or building systems need servicing or replacement.

Big data is shorthand for massive information collected from various places. By analysing data from multiple sources, predictive maintenance may forecast when a service of this kind will be required. Environment data, sensor readings, and machine records might play a role.

Machine or in-machine or MEMS sensors are embedded into machines to gather information. The efficiency of a device may be affected by factors like temperature, pressure, and vibration, all of which can be measured by sensors. Analysing the data collected by the sensors might help forecast maintenance requirements.

Maintenance records are used to keep tabs on the upkeep history of various pieces of machinery. In some instances, it may be possible to anticipate when specific equipment will require service by looking at their respective maintenance histories.

Environmental data is collected to comprehend the setting in which a machine operates. Decisions on when maintenance is required may be made more precisely if the data is analysed.

5. The Benefits of Big Data-Driven Predictive Maintenance

The use of big data in predictive maintenance has several benefits, including:

Reduced downtime: Predictive Maintenance, which can anticipate when repairs are required, may help keep rest to a minimum. If manufacturers can plan for maintenance requirements, they may schedule them during regularly planned downtime, reducing the number of unscheduled outages.

Reduced maintenance costs: By forecasting when maintenance would be needed, predictive maintenance may assist in lowering the overall expenses associated with care. Predicting the need for maintenance allows manufacturers to schedule it during scheduled downtime, reducing the likelihood that repair will be required during unplanned downtime.

Improved equipment performance: Improved equipment performance is one of the many benefits that may result from using predictive maintenance, which works to detect and address possible concerns before they become severe problems. Manufacturers can avoid the failure of their equipment by taking action as soon as potential issues are identified.

Increased equipment lifespan: By anticipating possible flaws before they become critical, predictive maintenance may help equipment last longer. Manufacturers can extend the life of their products by a considerable margin if they catch faults before they cause catastrophic failure.

Improved Equipment Performance: It is possible, with the aid of predictive maintenance, to maximise the efficiency of one's equipment, which in turn may assist companies in saving money. Predictive maintenance may be found here.

Lower Maintenance Costs: You may be able to avoid performing costly repairs or purchasing new equipment as often if you have predictive maintenance in place, which may save you money in the long term.

Increased Safety: Predictive Maintenance safeguards workplaces and the individuals working in them by predicting potential hazards and resolving them before they become dangerous. This helps to keep workplaces and the workers who work in them safely.

Improved Operational Efficiency: Predictive Maintenance has the potential to help businesses maximise efficiency by pointing out where they are losing ground and where they have room to grow.

6. Case Studies

Recent years have seen an increase in the implementation of data-driven preventative repair programmes. This trend is expected to continue. Examples include General Electric's (GE) Predix, a platform designed to use big data and analytics better to enhance the performance of machines and lower the risk that the apparatus may fail. GE Predix is only one example. Predix makes use of algorithms that are designed for machine learning to perform an analysis of data obtained from sensors that have been implanted throughout the machinery to anticipate the onset of problems with GE machinery. These sensors have been inserted throughout the machinery. Since GE utilises Predix, the company has increased its production and uptime while decreasing its yearly spending on maintenance. Consequently, GE has realised cost savings in millions of dollars.

One more organisation, Rio Tinto, which is in the mining business, is one of the many organisations that has adopted a predictive maintenance programme to enhance the efficiency of its concrete equipment. This was done to improve the company's profitability. Rio Tinto relies heavily on data analytics and sensor technology to closely check its machinery and warn off any potential breakdowns. Due to predictive maintenance, Rio Tinto reduced its overall maintenance expenditures by millions of dollars and its downtime by countless hours. The use of predictive maintenance was the driving force behind both of these enhancements becoming a reality.

7. Conclusion

Big data-driven predictive maintenance, in conclusion, is a powerful resource that may be used to boost output, save costs, and protect workers. Suppose a company collects and analyses enormous amounts of data created by sensors, equipment, and other sources. In that case, the company will be able to anticipate when problems may develop and take action to avert such issues. Building a predictive maintenance programme requires an initial investment of time and money. Still, there is a possibility that it may be profitable in the long term due to improved safety, decreased downtime, and increased efficiency. These benefits are compounded by the fact that building a predictive maintenance programme takes time. The use of extensive data in predictive maintenance leads tovarious benefits, including a reduction in the frequency of equipment failures, a reduction in related expenditures, a performance improvement, and an extension of the lifespan of the equipment. Sensors on machines, records of previous maintenance, and information about the environment of the production plant may be all potential factors that could assist manufacturers in anticipating when maintenance will be required and provide them with the opportunity to make preparations in advance. As the industrial sector continues to transform, big data applications, including predictive maintenance, are expected to become increasingly crucial. Organisations may lower their maintenance expenses by consuming big data in anticipatory maintenance.Improve the availability of their equipment, and increase their overall productivity.

On the other hand, putting this concept into action may not be as easy as it first seems. To maintain its competitive edge, a firm that wishes to continue operating in today's highly competitive market must staff its operations with data scientists, machine learning professionals, data collectors, and sensors. Many companies continue to see predictive maintenance powered by big data as a worthwhile investment, even if it has these drawbacks. In today's business world, more and more organisations are beginning to see the value in preventative maintenance.

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