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IOT and ML architecture for predictive maintenance in industry 4.0

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Abstract : ***To satisfy the demands of a more difficult and quickly changing industry, future manufacturing processes will need to be more adaptable. They must allow greater use of info, ideally all of it. Low-level details can be refined to actual knowledge for decision-making to encourage competition via timely decisions and informed. The automotive sector has a significant impact on economic and social growth. Since it is a common idea for colleges and research centers, the Industry 4.0 program has attracted a lot of support from the market and academic communities. Industry 4.0, as well as its synonyms such as Smart Production, Smart Manufacturing, and the (Internet of Things) IOT, have been recognized as significant suppliers to the digital manufacturing and automated climate. Industry 4.0 (I4.0), smart networks, (ML) machine learning, a branch of (AI) artificial intelligence, and PdM (predictive maintenance) methods are now frequently employed in factories to control the strength of manufacturing tools. Digital convergence for I4.0, computerized management, communication networks and information techniques, it is quite easy to gather vast quantities of process and functional situations information produced by various parts of tools and produce data for diagnostic and automatic fault detection with the intention of reducing downtime and increasing component utilization rate. This paper goals to offer a complete evaluation of current developments in machine learning methods broadly useful to PdM for smart manufacturing in I4.0 through categorizing the study based on the ML algorithms. In this paper future prediction of temperature is done using the time series analysis and multivariate analysis.***

IndexTerms **- Industry 4.0, IOT, Lean manufacturing, Predictive maintenance, CPA**

I. INTRODUCTION

Production systems of the future industries need to make better use of the information as well as the raw data [1][2]. To help decision-making, low-level data must be converted into smart services and usable data, must be incorporated.In recent years, the task of managing data, transforming it into information, and making wise computerized evaluations has gotten a bunch of interest. In partnerships including Smart Manufacturing Leadership Coalition 2016, Industry 4.0(Industry 4.0 Working Group 2013), Internet of Things (Atzori, Iera, and Morabito 2010) [3], the Industrial Internet (Evans and Annunziata 2012), and automation and cloud robotics, the emphasis has been on the overall architecture (Kehoe et al. 2015) [4]. While the concept is not innovative and has been on the program of theoretical study for several centuries with various interpretations, the word "Industry 4.0" has only recently been coined and is widely embraced not only in academia but also in industry. Professionals have coined the phrase "Industry 4.0" to describe how industries are now undergoing "The 4th Industrial Revolution." (I4.0). Industry 4.0 is a technique for transformingmanufacturing from a machine-dominated to a digital-dominated state. Industry 4.0 should be well known to achieve an effective transition, and a simple path map should be created and enforced.

With the introduction of I4.0, the idea of (PHM) prognostics and health management has developed an inevitable trend in the context of smart manufacturing and industrial big data; it also offers a dependable explanation for handling the health status of industrial tool. I4.0 and its main innovations are important for making industrial systems autonomous [5,6], allowing for automated data gathering from components and industrial machines. ML algorithms can be used to automate diagnosis and fault detection founded on the gathered data. However, selecting suitable (ML) machine learning methods, data types, data sizes, and tool to implement Machine Learning in manufacturing methods is extremely hard. Infeasible maintenance scheduling and Time loss may result from choosingthe wrong (PdM) predictive maintenance methodology, data size and dataset. As a result, the aim of this research is to introduce a systematic review of literature to discover current research and Machine Learning applications, thus assisting practitioners and researchers in selecting suitable Machine Learning methods, data type, and data size to obtain a feasible ML application. Since it was created to accomplish near-zero; hidden risks, faults, emissions, and near-zero accidents in the complete atmosphere of industrial methods, industrial equipment (PdM) predictivemaintenance can detect deterioration results. [7].

These massive volumes of data collected for ML provide a wealth of useful information and expertise that can help increase the overall competitiveness of manufacturing processes and system dynamics, as well as decision support in a variety of areas, most notably maintenance based on conditions, and health checking [8]. Now it is possible to gather huge quantities of process conditions and operational data produced from numerous parts of tools to be gathered in creating an automated (FDD) Fault Detection and Diagnosis [9] acknowledgements to recent developments in technology, communication networks, information techniques, and computerized control. The collected data could be used to establish further client-specific methodologies for intelligent precautionary maintenance practices, also recognized as PdM [10].

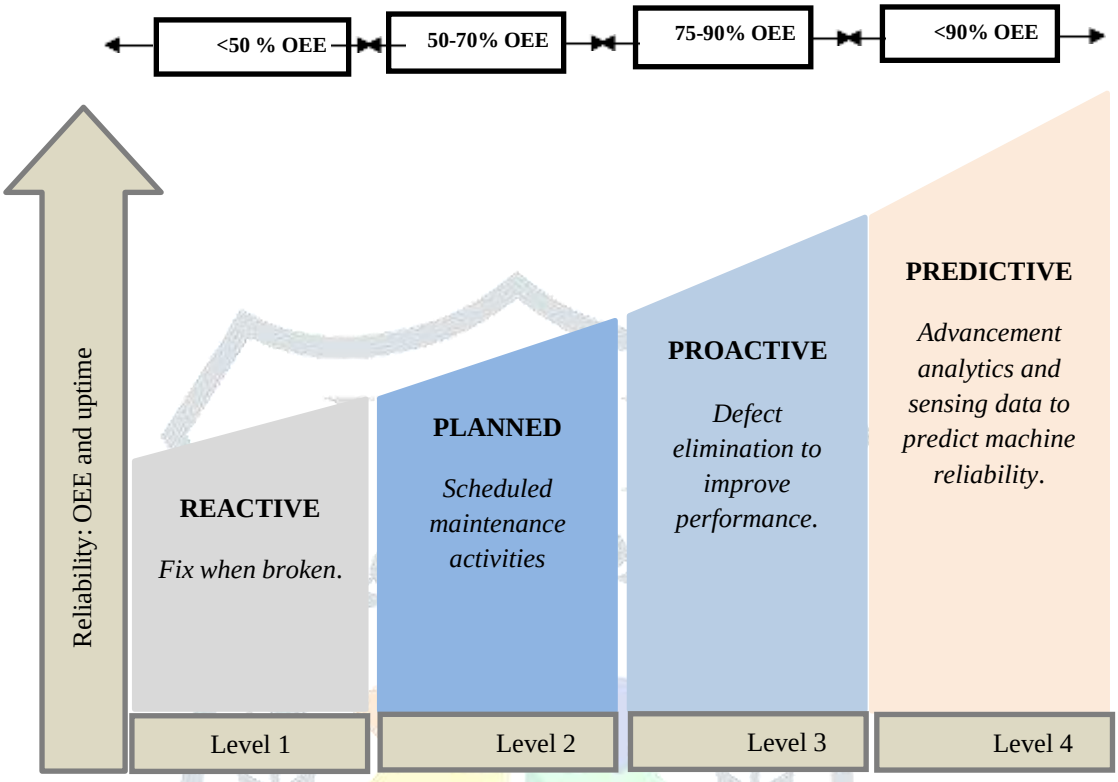

Figure 1: Maintenance type [1].

PDM is constructed on the premise that specific attributes of machinery could be tracked, and the data collected used to measure the equipment's remaining useful life. As a result, this form of maintenance strategy requires a range of major changes in the manufacturing and maintenance processes, all of which will substantially lower production costs [11]. First, since predictive maintenance is not dependent on periodic maintenance cycles tied to average lifespan, it can minimize the amount of excessive maintenance activities. As a result, the total number of maintenance tasks performed over the life of a system can be decreased. Because of the configuration in which some part is used in bigger equipment, for example. Both the reduction of fatal breakdowns and the reduction of excessive maintenance result in increased efficiency and less downtime in the manufacturing process. In comparison to traditional maintenance policies, Pdm can be considered an overall rise in productivity based on the accuracy of the prognostic approach used [12,13]. As a result, the aim of this paper is to deliver a complete overview of recent advances in machine learning techniques applied to PdM. This paper aims to pinpoint and categorize based on the ML technique considered, ML category, equipment used, system used in data acquisition, applied data definition, data size, and data form from a detailed perspective. This paper's goal is to give an overview of these initiatives, with an emphasis on I4.0 and Smart Manufacturing, as well as some application examples. Present and potential research problems for Smart Manufacturing will be recognized based on the findings. Temperature readings from IoT sensors deployed outdoor and inside an anonymous room have been collected. Because the device was still being tested, it was uninstalled or turned off numerous times during the reading period, resulting in some outliers and missing values.

INDUSTRY 4.0

The word Industry 4.0 refers to the fourth Industrial Revolution, a period in the growth of humanity's production systems. Industry 4.0's main goal is to make manufacturing – and allied industries like logistics – faster, more efficient, and more customer-centric, while also going beyond automation and optimization to discover new business prospects and models. The first three technological revolutions brought mechanization, energy, and IT to human development. Germany is one of the top technology production countries and has many of the most specialized suppliers and factories. In addition, two of three research and development funds are supported by the German government for industrial development, allowing industrial technology to rapidly expand. The passive machines and robotics have replaced the labor powers, which means that they are operated by an unconscious human. In 2012, the number of industrial robots in Germany was around 273 per 1000 employees, (K. Sector).

However, the use of personnel and supplementary services for monitoring, testing or effective servicing is indeed costly. Recently, the Internet of Things (IOT) and cyber physical system (CPS) have been used to link industry- related items such as content, sensors, equipment, goods, supply chain and consumers, which means that these required objects share information and control measures independently and autonomously with each other. German engineers understand that development has been a modern paradigm change, the so-called 'Industry 4.0,' in which consumers manage their own manufacturing processing.

Since then, Industry 4.0 is one of the world's most common manufacturing issues and has also been the fourth industrial revolution with severe potential effects on manufacturing. Many other developed countries are almost simultaneously conscious of this modern technological age. In China, the industrial growth strategy 'Made in China 2025' was issued in 2015. A business growth framework for the same reasons as Industry 4.0 was also developed [14] According to several analysts' studies and views, the future view of production, the latest business models and the framework architecture are discussed here to suggest the core ideas of Industry 4.0.

Since the late 1700s, when the first industrial revolution began, industrial maintenance and reliabilitytechniques have evolved. We are well into the fourth industrial revolution (Industry 4.0), and PdM (predictive maintenance) solution suppliers promise a reliability panacea.

IOT AND ML

Industry, infrastructures are all undergoing digital transformations. Whether it's referred to as the Industrial Internet of Things (IoT), Industrie 4.0. discrete and process manufacturing organizations have begun to reinvent their business models using accessible technology. Since IoT devices produce enormous amount data, conventional storage, data collection, and processing techniques may not be adequate. Patterns, habits, forecasts, and evaluation can all be aided by the massive amount of data. Furthermore, the heterogeneity of IoT data presents a new front for current data processing frameworks. As a result, new mechanisms are needed to unlock the value of IoT-generated data. ML is one of the best computational models for embedding knowledge in IoT devices. [15]

Machine learning can assist machines and smart devices in deducing useful information from data created by devices or humans. It can also be described as a smart device's ability to change or automate a situation or behavior based on experience, which is an important component of an IoT solution. In tasks like classification, regression, and density estimation, machine learning techniques have been used. ML algorithms and techniques are used in several applications, including computer vision, bioinformatics, malware detection, authentication, and speech recognition. In the same way, ML can be used in IoT to provide intelligent services. However, this paper, concentrate on the use of machine learning to architecture for predictive maintenance. [15]

THE VISION AND CONCEPT OF INDUSTRY 4.0

Many scholars believe that industrial developments entail a lengthy gestation cycle and address the following four elements, known as potential output visions:

- **Factory.** As one of Industry 4.0's key components, the future factory will include a new integrative facility, whichcan not only link and share information on all the manufacturing tools (sensors, actuators, motors, robotics, conveyors, etc.) but also make the factories responsive and intelligent enough to anticipate and manage their devices. Many manufacturing processes, such as product design, production planning, development engineering and development and services, can also be represented as hierarchical and linked, which means that these processes are not only managed by a decentralized structure, but are interdependently managed. This sort of futureplant is called the Smart Factory.
- **Business.** Industry 4.0 means the presence of a full communication network among different businesses, manufacturers, vendors, logistics, tools, customers and so on. Each section optimizes the setup in real time basedon the criteria and status of related network segments, allowing optimum benefit for all cooperatives with minimalcapital for sharing. Cost and waste, raw materials, CO2 emissions and so on can also be decreased. In other words,each co-operating segment affects the future business network which can attain a self-organizing status and relayreal-time replies.
- **Products.** The gains of Industry 4.0 would be a different form of industrial tool, that of smart devices. These goods are integrated into sensors, recognizable modules, and processors, which hold information and expertise toprovide consumers with practical guidance and transmits feedback on the application to the production system. Many features may be applied to goods with these components, for example calculating product status or customers, distributing this information, monitoring items, and evaluating the results based on it. In addition, a total development details log with a product support developer can be implemented to improve the process, forecast and maintenance.
- **Customers.** In Business 4.0, consumers would still have certain benefits. A new form of payment would be introduced for consumers. It enables customers to order any product feature with any number, even though thereis only one. In addition, also at the last minute, customers could without charge adjust their order and ideas at anytime during production. In the other hand, the advantage of smart goods helps consumers not only to know the product 's development details, but also to get guidance on the use according to their own conduct [16].

2. Lean Manufacturing

Lean Manufacturing can be better stated as a multi-faceted development strategy having a wide range of organizational processes aimed for the detection of customer-scope value-adding processes and enabling these processes to flow through the enterprise at the pull of the customer [17]. It originated from the conceptualization of the Toyota Production System (TPS) at Toyota Motor Company by Taichii Ohno 's initiatives (Ohno, 1988). The primary goal of lean manufacturing is to create a streamlined flow of processes to produce the finished products with little or no wasteat the required pace of customers. To define the dimensional structure of lean manufacturing, [17] conducted a systematic, multi-step approach-based analysis and built accurate scales to describe them. As described below, they quantified in ten variables the conceptual description and measurement of lean manufacturing.

1. **Feedback of Supplier:** Criticism and output of goods and services purchased from consumers to be conveyedregularly to suppliers to transmit knowledge effectively.
2. **Just-In Time (JIT) suppliers' delivery:** Just the quantity of goods needed to be supplied by suppliers at agiven time when they are required by customers.
3. **Supplier development:** Suppliers would be produced in collaboration with the producer to avoid confusionor a discrepancy in competence levels.
4. **Customer involvement:** Customers are the key drivers of a business, and high priority should be given totheir needs and expectations.
5. **Pull production:** An initiation of the need from the successor through Kanban should allow the predecessor'sproduction flow, signified as production of JIT.
6. **Continuous flow:** A efficient flow of goods should be formed through the factory without wide stops.
7. **Setup time reduction:** The period compulsory to adapt resources for product variations should be maintainedto the minimum possible extent.
8. **Total productive:** Successful periodic maintenance procedures should prevent the breakdown of machinesand equipment. In the event of failure, it is important to maintain a low rectification period.
9. **Statistical process control:** Product quality is of prime importance, from a system to a subsequent one, nodefect should be percolated.
10. **Employee involvement:** Employees are to be motivated with enough encouragement and entitlement to makean overall contribution to the business.

3. Predictive Maintenance

4. Predictive maintenance (PdM) has seemed like the ideal application for the Internet of Things (IoT), particularly for Industrial IoT (IIoT) and contexts where asset uptime is vital, and breakdowns can have serious consequences for a variety of reasons. It's no surprise that predictive maintenance is one of Industry 4.0's most often discussed use cases. PdM, on the other hand, is not only about smart manufacturing. Transportation, oil and gas, process industries in general, and numerous segments with critical power settings are among the industries/segments that use predictive maintenance as a use case. Industry 4.0, the arrival of modern numerical industrial technologies, seeks to make it possible for factories to produce higher-quality products at reduced costs more easily, more flexibly and more effectively (Industry 4.0 Working Group 2013). As in 'Predictive Maintenance 4.0' of Industry 4.0 [18] PdM has beenfeatured as a key theme. PdM tracks the health of equipment and indicates when a maintenance event will be required in the future, when the primary enabler for optimizing the availability of tools has been elevated to the highest priority.The factory wide PdM specifications are:

a. Strong infrastructure and fast platform for communication and processing of data.
b. Efficient diagnostic and prognostic engine for faults.
c. Manageable health index hierarchy from a factory-wide view.

Industry 4.0 is a collective concept for technology, paving the way for a smart factory and manufacturing that can beaccomplished by both IoT and CPS integration. A smart factory has smart-manufacturing scenarios; and by incorporating IoT, CPS, cloud-based techniques, and big-data technologies, smart manufacturing emphasizes man- machine collaboration and production logistics management. In order not only to achieve the goals of Industry 4.0, but also to achieve the target of No Defects, the authors suggested a platform called AMCoT. To act as the IoT agent, the AMCoT platform adopts the so-called CPA. The predictive maintenance system's major integrated components are as follows:

- **Cyber-physical agent (CPA*):*** CPA plays a significant role in the AMCoT platform by
  a) Collecting data and dealing with physical objects, cyber networks, and human operators,
  b) identifying all the physical objects, and
  c) supporting intelligent applications. CPA is composed of CPA control kernel, communication service, data collection manager (DCM), data collection plan (DCP), data collection report (DCR), equipment driver (ED), application interface (AI), and database.

Advanced manufacturing cloud of things (AMCoT): AMCoT offers a cloud-based network between the sellerand its customers to communicate and exchange all knowledge about items. In this way, the seller will create attractive after-sales services, such as building AMCoT on-demand services / models directly, fanning out AMCoT real-time models, and tracking all machine tools through AMCoT to minimize maintenance costs.AMCoT offers a forum for bridging suppliers, consumers, and manufacturing tools with technology support.

5. Review of Literature

A literature review is an important component of every research project. The writers used a similar analysis technique in this article. First, related sources of publication about innovations in the fields of Industry 4.0 and smart manufacturing were established for this article. The authors cited articles from the Web of Science (WoS) website, which features many prestigious publications such as Emerald, Taylor and Francis, Springer, IEEE, and Elsevier. Thesystematic analysis approach followed a six-step procedure, as seen in Fig. 2. [19,20]

O'Donovan et al. (2015) [21] published a survey that analyzed and rated the papers, indicating research progressrelevant to Big Data and Industry 4.0. They start with a thorough mapping study of Big Data in manufacturing. The mapping's findings for two study questions piqued our interest: "What kind of analytics are used in big data in manufacturing?" and "What kind of analysis is done in big data in manufacturing?" Moreover, the agitation in comingfuture works mentioning the necessity for repair and diagnostic studies aided in the continuation of this article

In terms of maintenance, [22] presented a technique and framework that described a CPS template for Big Data for PdM and demonstrated that it is possible to render the degradation of an asset visible to human users by leveragingtechnology. The same can be said for report [23], which included concepts, implementations, and challenges in CPS domain forms. Current improvements in industrial information science surrounding Big Data environment, CPS, and Industry 4.0,' according to [24]. Similarly, [25] present Big Data's effect as a knowledge domain, categorizing worksinto twelve technology fields and six Big Data challenges. In terms of maintenance, [22] presented a technique and framework that described a CPS template for Big Data for PdM and demonstrated that it is possible to render the degradation of an asset visible to human users by leveraging technology. The same can be said for [23]. report, which included concepts, implementations, and challenges in CPS domain forms. Current improvements in industrial information science surrounding Big Data environment, CPS, and Industry 4.0,' according to [24]. Similarly, [25] present Big Data's effect as a knowledge domain, categorizing worksinto twelve technology fields and six Big Data challenges.

According to recent studies, the number of works implementing Industry 4.0 models, platforms, technologies,usage cases, and other facets is growing [26]. As addressed in this article, the techniques provide a wide variety of applications in fields such as process and preparation (value increment and waste reduction), supply chain, transportation and logistics, health and safety, product design, and, most notably, maintenance and diagnosis. For example, in their guidelines,) [27] discuss their use for energy utilization reduction, endwise product engineering through the complete supply chain, custom manufacturing support, telepresence, and unexpected supplier adjustments during growth. Energy conservation was also discussed in the work of [28]. [29] studied the trends of process improvement that developed because of the industrial revolution.

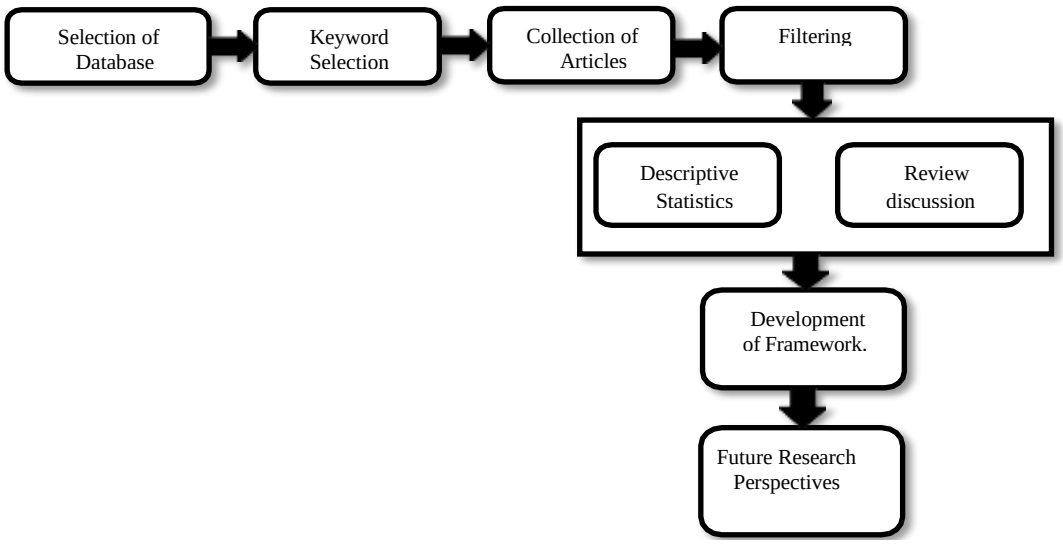

Figure 2: Research process adopted for the structured literature review.

Another interesting application, as described by [30] is the development of simulated worlds utilizing enhanced experience, which may be used to assist operators in a dynamic manufacturing setting. [31]. built on this notion in their study. This project investigates the usage of Industry 4.0 concepts for asset predictive management, a crucial element of a company's effectiveness and product quality [32,33]

The number of case studies in the literature is increasing as PdM becomes more commonly used. Such as,) [34] identified a cloud-based tool for condition tracking of a cutting system, through which the machine's health status is communicated to the operators through a web interface. [35], which is more relevant to our function, employs a Kalman filter to approximate the state of a DC motor for PdM purposes. As mentioned by Prajapati et al. (2012) [36], this approach has the downside of being complex and computationally expensive, rendering it unsuitable for sensitivesystems. Papers by [37], [38], and [39] provide additional case studies.

They discuss the need for predictive maintenance in the field of Industry 4.0, but they don't go into detail aboutit. They explain CPS, Big Data, and problems associated with large volumes of data, but they don't go into detail aboutit [40,41,42,43]. Paper discovered a few technical papers that provide a more detailed description of PdM solutions and services [44]. Except for two recent systematic reviews that explicitly cover ML and implementations of data- driven approaches in PdM, none of them specifically concentrate on PdM implementation [45,46]. Despite the fact that the subject is not as broad as suggest in this article. paper looked at and identified a few key topics for PdM researchers.

Data collection, pre-processing, wear detection, and indicating out the probability of collapse are all common themes in works that approach PdM. [47,48]. This definition is remarkably similar in works about PHM and the periodof study, observation, and action that it entails. [49], PHM has been examined in the literature by investigators from various engineering fields to improve the dependability, accessibility, protection, and cost-effectiveness of engineering properties. Authors such as [34] see advanced forecasting methods as an integral part of their study. Theexplanation for this review's focus on PHM content is that.

These works focus on various strategies for deciding the condition of the machinery, the majority of which come from the (AI) Artificial Intelligence or (ML) Machine Learning sectors [50]. Machine Learning methods are data-focused methods capable of detecting complicated and non-linear trends in data and constructing models from them for regression, classification, detection, or estimation [51,52,53]. Among these methods are Support Vector Machines, Decision Trees, Neural Networks, and so on, with the model selected depending on the following criteria: the kind of data it must operate with, the operating conditions, and the type of outcomes it must [54].

In this paper, it recommends a PdM model that uses an ML technique called a Discrete Bayes (DBF) to transform data from sensors, systems, and domain experts into details about the machinery's deterioration condition and potential actions. The filter naturally models the knowledge latent in these types of processes, offering a valuable measure of confidence in its result. Another significant advantage of DBFs over other ML alternatives is their resistance to fluctuating and noisy data. The suggested filter will also benefit from practice, addressing the time constraints imposed by industrial environments. Other filters, such as the Kalman filter its extensions may be considered as well, but they either depend on the underlying system's linearity assumptions or involve the calculus ofcomplex Jacobians to linearly approximate its dynamics and propagate uncertainty. This study is being done as part of the SiMoDiM project, with an emphasis on the Steckel mills used in the Hot Rolling method to manufacture stainless steel. To the best of our understanding, this is the first paper discussing the predictive management of SteckelMill components. [55]

The RF algorithm has been discovered to be the most widely used ML method for predictive management having been used on a wide range of components, industrial equipment, or systems, like turbofan engines, aircrafts, rotating machineries, rotor bar-LS-PMSM, production lines, semiconductors, industrial pumps, cutting machines, supermarket refrigeration systems, (HDD) hard drive disc, wind turbine, and vending machines. CNC machines, windturbines, aircraft, and semiconductors seemed to be the authors' main focus. [56]

The 4th industrial revolution, also recognized as Industry 4.0 (Germany/EU) and Smart Manufacturing, has received a lot of attention (USA). The traction and prominence that both programs (and related ones in many other countries) have achieved in recent years demonstrates the dramatic, paradigm-shifting change that the automotive industry and manufacturing science are undergoing today. I4.0 and Smart Manufacturing are terms used to describe the shift to a highly data-focused production network with improved integration and adoption of knowledge and networking technology thus holding people in the loop. Among the goals are energy conservation, sustainability (social, economic, and environmental), agility/resilience, and consistency and performance. [57]

Despite the availability of reliable testbeds, I4.0 and Smart Manufacturing are both in their infancy. Given thefunding agencies' interest and accessible grants, as well as the strong interest from business (both major corporations and small and medium-sized enterprises), rapid developments in this area are anticipated in the near future. Because of their interdisciplinary nature, advances in basic research fields could make their way to commercial use more quickly than in previous years. This may be a chance for researchers who haven't had any contact with practical sciencein their area to collaborate with researchers from other fields to sectors to see their study come to fruition. [57]

Industry 4.0 would allow predictive and smart manufacturing in the future. An industry 4,0 factory's machinesare joined as a joint group, allowing for a wide range of predictive maintenance options. The development of predictive maintenance, its technical problems, and its future in the Industry 4.0 ecosystem is discussed in this paper. In the oneside, the field of smart factories, industrial big data, and cloud computing is enhanced and accepted in the Industry 4.0 period, paving the way for predictive maintenance. Predictive maintenance, on the other side, can play an important role in potential maintenance operations and will assist in meeting Industry 4.0's requirements for smart production and self-aware robots [58].

6. Research Gap

In the literature various of the forms are considered for the achievement of the goals of the industry 4.0 with the consideration of various systems and frameworks like lean management, smart data management, predictive maintenance, etc. While in none of the work the integration of the lean management with respect to the predictive management is being considered. As in predictive management the purpose of the system working is for the predictionof the coming process and requirement steps in terms of the data, tools, and other requirements. And also, at the same lean management will help the industry to remove out the waste from the organization, which directly will affect the performance of manufacturing process.

Beyond this all the gap identified in the literature is about the consideration of the optimized techniques for information system in terms of the decision making, also for the integration of the optimization process online and information visualization. In the information system available the data first is supposed to be classified and then it to be picked for the decision-making process for which some specified machine learning techniques are supposed to beopted. In the current work the major focus is on the optimization process in terms of the performance, energy, etc. andalso considered the decision-making process via data classification.

7. Objectives of the Research

i. To study and evaluate about industry 4.0.

ii. To study and evaluate the concept of the lean management and predictive maintenance.

iii. To design an integrated system as predictive maintenance module considering the principles of the leanmanagement.

iv. To validate the research work using the comparison strategy with previous works done.

8. Research Methodology

Industry 4.0 is all about the automation of the overall process and also about the inclusion of the techniques like IoT, Cloud, AI, etc. over the traditional system for manufacturing process. Complete manufacturing process is the integration of the various tools, machines, techniques working together for an integrated outcome. In the various of the frameworks towards the achievement of the industry 4.0 predictive maintenance is one which works towards the enhancement of the manufacturing process with efficient utilization of the resources used for the complete process. The maintenance process includes the consideration various processes like data collection, data storage, dataprocessing, and checking working of the tools running for the manufacturing process.

Based on the previous recorded data the system provides a decision for the maintenance related steps, other than the maintenance related process the machine should be made to react for the lean management which works for the betterment of the organization is one of the better tools considered in the industry 4.0. In the prediction system themodules like Cyber-physical agent (CPA) and Advanced manufacturing cloud of things (AMCoT) are integrated together for better prediction process. In the process of predictive maintenance, the five principles of the lean management are to be considered for the better efficiency and ensuring the integration level of the industry 4.0 and lean.

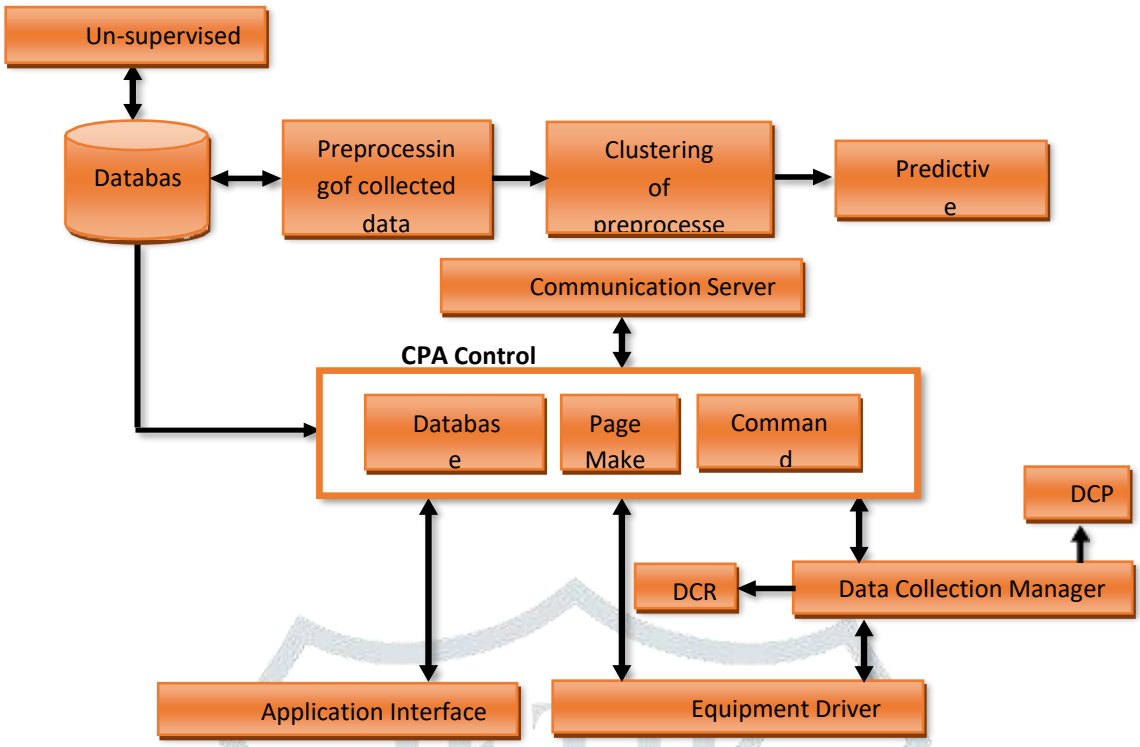

Figure 3: Working Architecture of the predictive system.

The complete research work processes in three different modules as, Data gathering/collection, Dataset training and Decision making. For the data gathering the process defined in CPA architecture (Y. Chiu *et al.*, 2017) is considered which is having various modules integrated for the data collection. CPA architecture is composed of CPA control kernel, communication service, data collection manager (DCM), data collection plan (DCP), data collection report (DCR), equipment driver (ED), application interface (AI), and database (Cheng et al. 2016).

The un-supervised learning technique is considered for data set training, where the algorithm is expected to analyse the actual data with unsupervised machine learning to identify similarities, patterns, and correlations in the data to explore and learn about relationships within the data. The training of the dataset is then accompanied by a clustering process, clustering is the method of identifying correlations in un-labeled data in order to combine related data items into a cluster together.

The work majorly focuses for the lean manufacturing which is the integrated contribution of the various modules likesupply chain, process/operation, human employment, control and human factors, predictive maintenance, etc. In the present work the major consideration will be towards the smart- supply system and lean manufacturing with the help of the predictive maintenance in temperature analysis. In the proposed study the predictive system is to be considerednwhich is optimized with the help of the learning process to present the smart supply system and work towards the leanmanufacturing considering various parameters that defines the lean manufacturing.

9. Implementation Results

In the datasets, it has the temperature readings from IoT devices installed outdoor and inside of an anonymous room.

Dataset details:

- **temp**: temperature readings of the dataset.
- **out/in** whether reading was taken from device installed inside or outdoor of room.

Finding of the dataset:

- the temperature difference between interior and exterior
- trend or seasonality in the data
- forecasting future temperature by using time-series modeling
- characteristic tendency through year, month, week, or day/night

Time series analysis of the temperatures.

1. Inside temperature is composed of a single distribution, whileoutdoortemperature is composed of multipledistributions.
2. The temperature indoor the room is kept constant by the air conditioner, but the outdoor temperature iseasily affected by time-series factors such as seasons.

3. The outdoor temperature has a larger time series change than the indoor temperature.

According to this observation, India has four climatological seasons as below.

- Winter: December to February
- Summer: March to May
- Monsoon: June to September
- Post-monsoon: October to November

We can create seasonal variable based on month variable.

The time series analysis to predict the future temperature, inside and outdoor the industries.

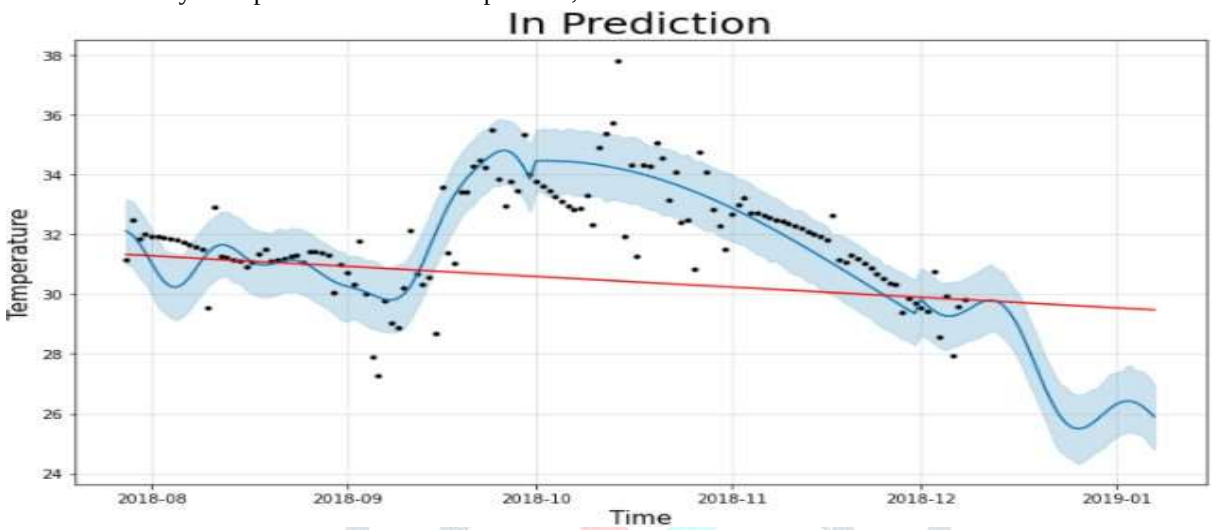

Figure 4: Prediction of inside temperature.

Result 1: Figure 4 shows the inside temperature prediction of the industry based on the monthly basis.

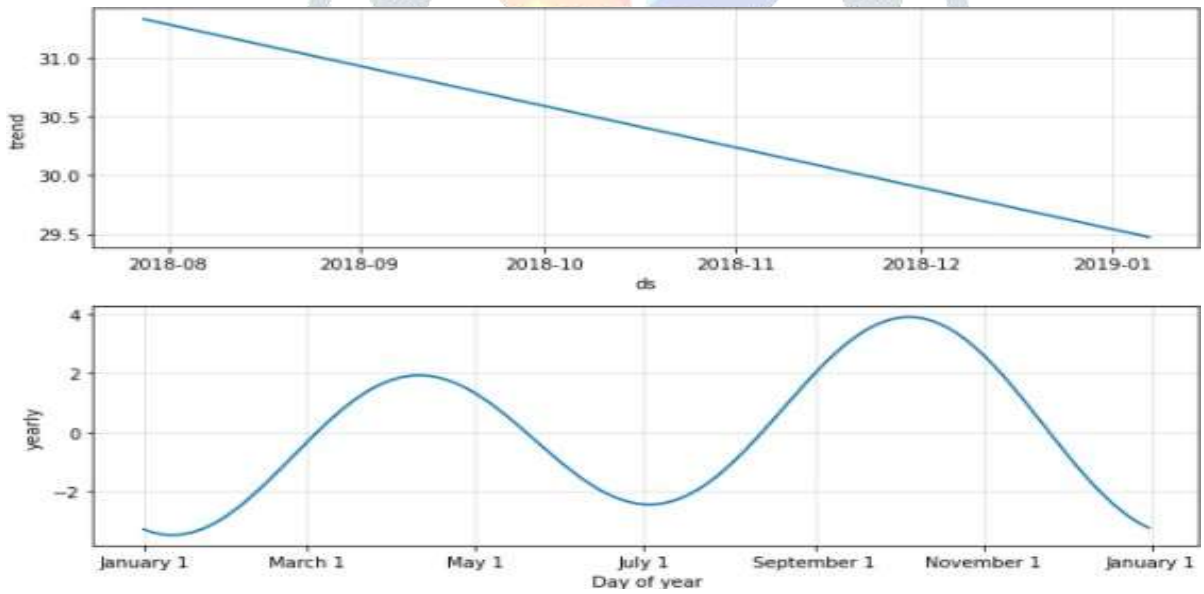

Figure 5: Trend of inside temperature

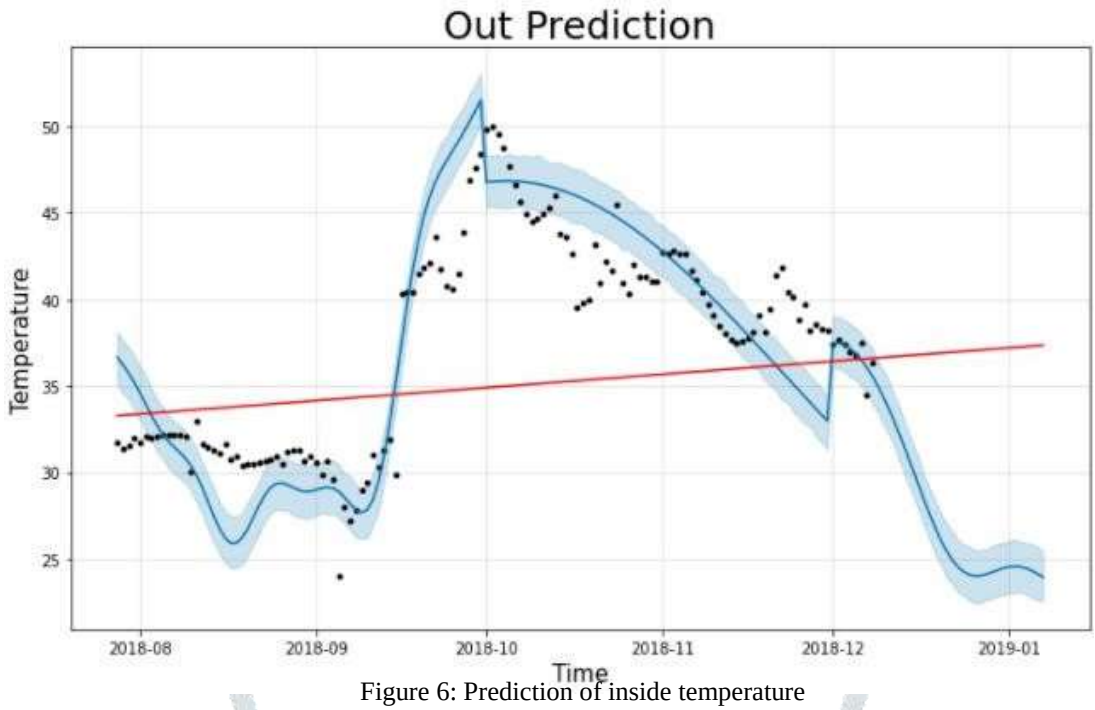

Figure 6: Prediction of inside temperature

Result 4: Figure 7 shows trend of temperature according to seasonality outdoor.

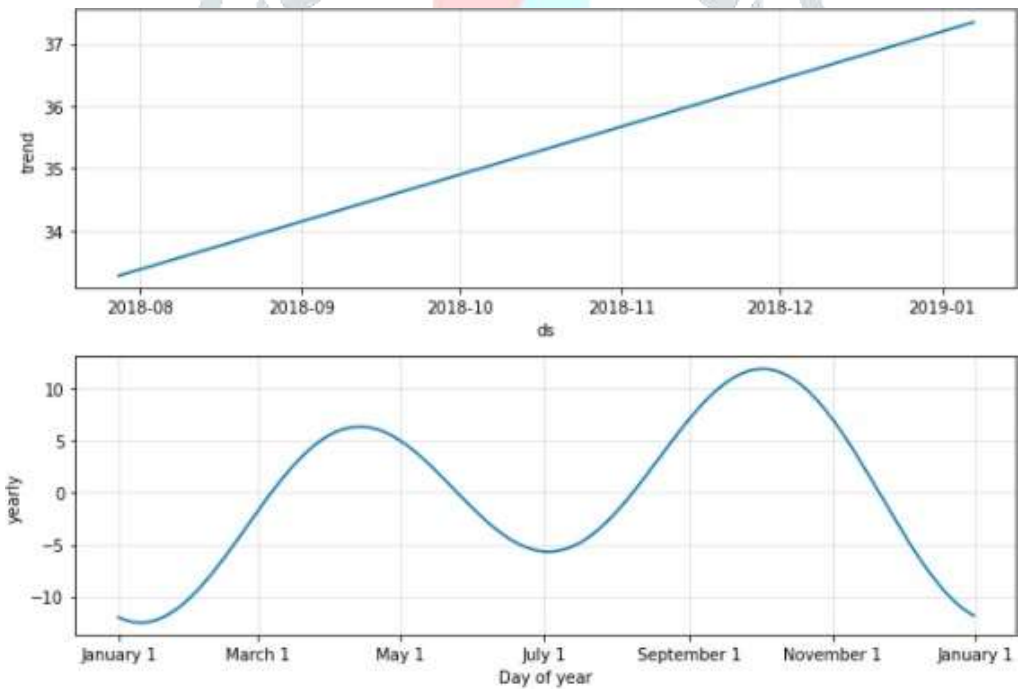

Figure 7: Trend of outdoor temperature

10. CONCLUSION

The presented work focuses on the predictive system for the lean manufacturing as major goal. Lean manufacturing goes with the consideration of the customer involvement, supply system, employee involvement, continuous flow of the end results. The work considers the decision-making system where the un-supervised learning techniques is being used for training the dataset as the data generated is a un-labelled temperature data generated by different sensors, manual notations or machine generated temperature data and the outdoor fluctuated temperature data. The data after pre-processing is clustered to generate the data in different groups based on similarity, which is then is being used for the decision-making system for the future prediction of temperature. The system is also trained for making the decisions for the maintenance related decisions about the machines operating. The end outcome of the system is the seasonal information of the temperature for analysis of the future temperature prediction. The forecast model is implemented

with the indoor and outdoor temperature. Annual temperature swings can have a greater impact on outside temperature than on indoor temperature. Outside temperature is made up of numerous distributions, whereas inside temperature is made up of a single distribution.

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