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PREDICTIVE MAINTENANCE IN PRINTING INDUSTRY

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Abstract

The value of Indian print industry is estimated to be over 296 billion rupees in 2019. And is expected to go up to over 370 billion rupees by 2022, in which the newspaper industry contributes 60%[1]. In fiscal year 2018, print circulation revenue in the South Asian countries was led by the Hindi speaking market with revenue of almost40 billion rupees. The employment has also increased over the last decade. Similarly, the printing unit needs to be rigorously supervised and highly maintained on a daily basis for preventing unexpected faults (preventive maintenance), which requires a good number of staff members. Even though Predictive Maintenance as a Service (PMaaS) has started to boom now. There are hardly any facilities for it in this industry. Therefore, servitization in this market has good scope.

Key words: Print Industry, PMaaS, Servitization, Product Servitization

Introduction

In India, the net worth of Indian newspaper industry is 177.6 billion rupees, with 7.2% growth per annum, and the average newspaper printed by a press per hour is 1,00,000. And the minimum price of a newspaper is Rs.2. Even a minute problem takes minimum 15 minutes to resolve that issue and start the printing work again. The press faces a loss of nearly Rs.50,000 whereas in reputed newspapers their loss could be even higher.

Conventionally, Preventive Maintenance is the method in which the print industry is being supervised. It is done on a scheduled basis, whether upkeep is required or not maintenance will be done. Preventive maintenance is designed to keep parts in good condition, but does not work on a necessity basis [2]. Hence, it can be seen that one among the important industries of a country still has an ineffective cost strategy.

On the other hand, Predictive Maintenance is early detection of faults in equipment operation. With enough data, changes can be analysed to reveal maintenance requirements before they affect production or machine uptime [3]. Predictive Maintenance sensors constantly monitors, records and analyse numerous aspects of equipment operation to provide deeper insights. On the whole, it helps users avoid downtime and loss due to equipment failure [4]. It also provides a cost effective alternative when compared to keeping and training an in-house maintenance team by offering support on a scheduled basis [5]. In this method maintenance is done as per necessity, by identifying issues at the nascent stage before they can interrupt production. Even if shutdown is required, it will be shorter and more targeted.

Nowadays B2B companies have started to shift from providing products to collaborating them with services. Example: Automobile (Rolls-Royce) – “Power by hour”, Xerox – “Pay per hour”. This is the strategy that has started to boom in servitization, in which focus has turned towards service centred products.

Product Servitization helps in alleviating product related burden and also helps in reducing costs up to 25-30% [6]. Since this highly focuses on end user experience, shares responsibilities of the consumer, seems appealing for the consumer. Thus, following this B2B strategy is sustainable and simultaneously increases the margin of both and seller with a better competitive advantage. Thus, this paper focuses on providing Product Servitization for the newspaper industry by providing them with intelligent printing equipment, in which charge is made on the basis of “Copies per hour”. In simple words it focuses on implementing Predictive Maintenance as a Service in Printing Industry.

Working

Servitization speeds up such that in 2022 most manufacturers will acquire more than half of their revenue via services. With the manufacturing sector increasingly being commoditized is the key to sustain and profit in the market [7]. Hence, many manufacturers are switching to service focusing business models [8]. With advent of this B2B strategy new business opportunities can also be created. Delivering manged print services (MPS)4 requires system integration, application development and consulting capabilities [9].

The primary aim of the project is to create a platform that would connect the data from printing equipment directly to the service sector of the organisation from which the equipment has been rented, through which they can have a check on the working condition of their equipment by following Predictive Maintenance [10]. Various data are collected by the sensors and gets stored in the cloud [11][12].

By using those values Remaining Useful Life (RUL) is calculated on real time basis to get precise and reliable results with short response time. And when RUL of the equipment gets decreased and starts to go beyond the optimum working time of the equipment it notifies the user through a warning displayed on the website (both consumer and service sector gets notified) and an alarm ringing at the printing press. Hence, a double check is kept so that there is no chance of missing any intimation [13].

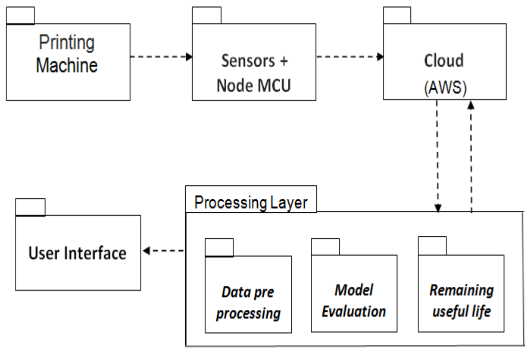


Fig 1: Block Diagram

SETUP IN SHORT:

a. Sensors are placed in various parts of the printing machine.

b. Data from all sensors are collected and then stored in cloud.

c. Dataset obtained in the cloud is then pushed to processing layer.

d. In the processing layer data is pre-processed, then the ML model evaluates and finds the RUL

e. The output of the processing layer is again stored in the cloud and displayed in a user interface platform.

II.A. Hardware Components

1. **Node MCU (ESP8266):** Node microcontroller chip is an inexpensive IoT platform. This board can be effectively programmed with Arduino IDE using C language for this prototype. Once the code is fed into it certain connections must be made in Node MCU chip and upload the program to get the desired result. This acts as connector between sensors and cloud as it helps in transferring data [14].

2. **Temperature Sensor:** It is an electronic system that measures the temperature of its surroundings to monitor the changes in the temperature [15]. It has 2 metals that creates voltage when there is a change in temperature. This sensor is to be placed at the outlet of the coolant from the system which helps in measuring the average temperature of the overall system.

3. **Pressure Sensor:** Pressure sensor acts like a transducer which contains a sensing element with 4 strain gauges employed on it [16]. Those are arranged in a Wheatstone bridge where 4 equal resistors are used which change by equal magnitude. This sensor is used to measure the blanket pressure and compressor pressure of the system by placing them on the blanket of the web offset and at the suction tube of the compressor respectively.

4. I**nductive Sensor:** An inductor creates an EMF when current flows through it which uses the current generated to detect nearby metal substances. These are used to measure the alignment of the cylinders which is paced at the top of the main tower [17].

5. **Laser Distance Sensor:** It operates by calculating the time taken by a pulse of laser light to be reflected by a target and return back. Lasers are used for measuring distances as they travel at constant rates through the atmosphere, and can travel greater distance without losing its intensity [18]. This sensor is used to measure the diameter of the cylinders and are placed beside a roller of each unit. Thus, by knowing the variation in diameter dust accumulation due to improper cleaning before every run can be found.

6. **Ultrasonic Sensor:** It helps in measuring the distance by using ultrasonic waves, which is estimated by calculating the time interval taken from the emission and reception of sound waves [19]. This sensor is used to measure the coolant level and web break. Hence, it is placed in the coolant tank and main tower respectively.

The main ideology is to collaborate these 12 proposed sensors with the existing web offset printing machine [20]. Thus, implementing these in the specified position of the machines and setting up this system in the users` environment with a Wi-Fi connection in their premises for transferring real-time data to the cloud is the deployment required to be done in hardware part.

II.B. Software Components

1. **AWS IoT Core:** This platform helps to link IoT devices to AWS Cloud. It can collaborate with billions of machines and can process other machines reliably and securely [21]. It makes it easy to apply to Amazon SageMaker and Alexa Voice Service to create IoT applications which collect, process and analyse data produced by connected devices.

2. **AWS IoT Analytics:** It is fully governed service that implements analyses and scales to support up to petabytes of IoT data without worrying about the cost and complexity required to create an IoT analytics platform, With AWS IoT Analytics, we can easily analyse data and build quick and responsive IoT applications. It filters and enhances IoT data for analysis as time series data [22]. After setting up the service to collect the data, mathematical transformation is applied to process the data and enhance it with device specific metadata such as device type and location before storing the processed data. It makes it simple to develop programs with machine learning (ML) by including built in templates for regular IoT use cases.

3. **AWS SageMaker:** It helps data scientists in building, training and deploying machine learning models quickly. This is used to easily connect the data from IoT Analytics so that there will be deployment with higher runtime in GPY and can also be stored, retrieved and processed in the cloud.

ML program must be pickled to load and run the program whenever needed. Then the whole software file will be converted into a docker file, so that it will be easy during deployment. Using AWS Kubernetes, data from different users can be clustered and processed [23]. Thus, this helps deploying this product for a wide range of users. To deploy this in reality in a printing press one has to just sign up and select a subscription plan on the online platform.

Methodology

The objective of the model is to find the RUL (Remaining Useful Life). The subjective estimate of remaining time a component can function in desirable state before the need for replacement or maintenance is called RUL. It is done using observations or estimation of average of different parameters.

By taking this into consideration, one could schedule maintenance, improve functional efficiency and prevent unexpected downtime [24].

Initially while calculating RUL for printing machines we should be attentive and aware in handling unique events as we don`t have enough dataset [25]. Hence, for prototyping purposes a similar dataset was collected from Kaggle platform. The data was used to predict RUL using different algorithms and observations were noted [26].

Since real time data is to be used, the data collected will be in the form of time series data. Time series forecasting is a method in which time series data are used to make future predictions with help of historical values.

The time series dataset to be used consists 16 columns namely timestamp, temperature, blanket pressure, compressor pressure, pH, alignment of cylinders, diameter of cylinders, coolant level, web brake, GSM (Gram per Square Meter), Number of Copies/hr, breaking factor, in which blanket pressure and diameter of cylinder itself has 2 and 4 columns respectively.

All the parameters except GSM, number of copies/hr, breaking factor are to be collected using sensors whereas these 3 are taken as input from the users through UI.

After training various time series suitable algorithms and finding their accuracies, algorithms namely Naïve Bayes, KNN, SV, LSTM had better accuracy when compared to others.

- **Naïve Bayes Algorithm:** Naïve Bayes allot a probability to the data in targeted column, this distribution is then combined as a single prediction.
- **KNN Regression:** It helps in finding average of the targeted numerical of nearest neighbours.
- **SVR:** It is also called as Support Vector Regression. This uses the data points and output points to form a two-dimension hyperplane and form decision boundary.
- **LSTM:** Long Short-Term Memory is a unique Recurrent Neural Network (RNN) to alleviate the gradient disappearing issues [27]. It can learn long term dependencies with the help of gates.

After implementing and comparing the results of all these 4 algorithms on the sample time series data, LSTM algorithm was selected for further proceedings as it had better accuracy with better speed and run time for a large dataset

Result And Inference

Developing this hardware is slightly costlier than the existing printing machines in the market, due to the sensors that are being used. Similarly, real time dataset has to be collected before launching this in the market to complete developing this product, since it is unavailable.

Even though these remain to be as a point of constraints of the product these can be converted into opportunities using the strategy that has been devised (renting in PMaaS).

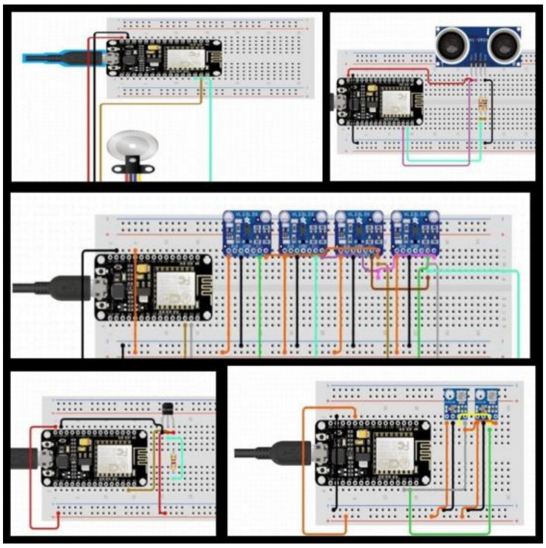


Fig 2: The chip diagram for the sensors used prototyping this model

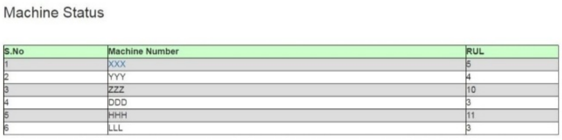
Machine id:
XXX

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14
Sensor 1														
Sensor 2														
Sensor 3														
Sensor 4														
Sensor 5														
Sensor 6														
Sensor 7														
Sensor 8														
Sensor 9														
Sensor 10														
Sensor 11														
Sensor 12														
Sensor 13														
Sensor 14														
Sensor 15														

Result:
Error due to: Parameter

Assign to:
Member 1 Assign

Fig 3: The mean sensor data for each day of specific machine is tabulated and recorded for future use and is used for analysis



Machine Status

S.No	Machine Number	RUL
1	XXX	5
2	YYY	4
3	ZZZ	10
4	DDD	3
5	HHH	11
6	LLL	3

Fig 4: Overall RUL of each day of all the machine that company holds can be viewed by the service department and can be used to compare and visualise to take actions accordingly.

If the RUL reaches a certain level (15-7 days will be optimum for this prototype), then maintenance can be scheduled accordingly thus failure can be avoided.

The created ML prediction model helps in forecasting RUL of the real time time-series data has been done using LSTM algorithm which gives an accuracy of 70% on an average, which indicates its reliability. Thus, it can be implemented and can help in making better profits.

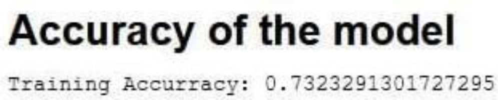


Fig 5: Accuracy of ML Model

Conclusion

Predictive monitoring thus increases productivity, growth in revenue and profit and improves response to customer needs.

Thus, in this both the end user and the service provider are profitable. End user can earn with less investment, whereas a service provider has the chance of using this product as a service which makes them earn continuously. Thus, using these strategies and satisfying both the ends equally can become the unique value proposition.

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