Smart Preventive Maintenance- A Review

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Abstract

The maintenance function would help extend the useful service life of a machine tool. Maintenance can be broadly classified into break-down, preventive, and condition-based maintenance. This paper intends to (i) study the different techniques proposed by researchers for the maintenance of machine tools, (ii) understand their merits and limitations, (iii) identify the research gaps (iv) provide the future directions. The present research has identified that many of the techniques proposed by researchers were applied in manufacturing and Electrical power distribution systems. The paper concludes that much research is required for developing preventive maintenance policies in other domains, including textiles, aerospace, defense, and machine tools manufacturing.

1. Introduction

Many sectors, including manufacturing, have been practicing maintenance functions to extend the useful service life of a machine tool (Dalenogare 2018, Frank 2019, Aivaliotis 2019, Aivaliotis 2021, Grall 2021). The maintenance function would help a company meet customers' expectations by making machines or machine tools and equipment available most of the time. This would make the device available whenever it is required for service. This would help in enhancing the availability of machine tools. This would make a manufacturing line consistent in delivering quality products. This, in turn, would increase the manufacturing company's reputation in front of the customer. This might result in repeat orders from the customer. This would create customer goodwill.

2. Literature review

The following paragraphs discuss the maintenance techniques proposed by different researchers, used by other sectors.

2.1 Manufacturing

A machine becomes unavailable because of multiple reasons. One reason can be the malfunctioning of a component of the machine tool. When this scenario prevails, either a device may become temporarily or permanently unavailable. This would result in unnecessary downtime till the machine becomes functional. This is going to affect the productivity of the entire manufacturing line. When a device becomes unavailable, the production manager may have to reschedule the machining of the component either when the machine becomes available or if the component has no time. The part will have to be machined on some other available machine. Re-scheduling is very difficult as it would disturb the machining of other components in the line. This example signifies the importance of the maintenance of a machine tool. Thus, when a machine becomes unavailable, this would not result in downtime of the concerned machine tool but would also increase the waiting time of the work-in-process as the work-in-process may have to be carried to another machine for subsequent processing. In a process layout, this would further complicate the scenario. The commonly used maintenance practice is to subject the device to maintenance when the machine becomes unavailable. This practice is known as Breakdown maintenance. To overcome some of the drawbacks of Breakdown maintenance, preventive care came into existence.

During preventive maintenance, a machine will be subjected to scheduled maintenance. So that machine will not be available during maintenance. The production manager will decide the frequency of preventive maintenance by looking at the type of machine and the criticality of the machine. The criticality of the device will be determined by considering many factors, such as complexity, number of moving parts, size of the device, cost of machine breakdown/ or machine downtime. With the advent of Industry 4.0 and Artificial intelligence (AI), many researchers have proposed schemes for the maintenance of machines involving ML and AI for predicting the remaining service life of the machine tools. This method uses sensors to collect data about the machine components' different components. The technique is called condition-based maintenance. Many researchers have demonstrated condition-based monitoring of machine tools.

Researchers have proposed methods that involve using statistical-based and symbol-based AI technologies to develop machine degradation models using industrial data collected from heterogeneous sensors. Reliability assessment of many modern power grids is becoming complex and computationally expensive. One researcher has proposed a technique for estimating the reliability of modern power grids using machine learning and Monte Carlo simulation (MCS) methods to overcome this problem. Machine learning-based techniques could classify the power grids into success or failure states.

Many production managers face the most common problem in manufacturing industries: choosing the correct maintenance method for given equipment. One researcher (Saaty 1996) has proposed the Analytical Hierarchy Process (AHP) to identify critical components in a machine. Using AHP, the production manager will determine which part requires which type of maintenance, intending to reduce the total cost of care. The main advantage of using the AHP technique is that it would help a production manager to focus more on critical components.

Another significant area concerning preventive maintenance in manufacturing is tool condition monitoring. A machine tool uses different types of cutting tools during machining a component. A quality product can be made only when the cutting tool, machine tool, and the raw material is also in good condition. This shows the importance of tool condition monitoring in product manufacturing. A cutting tool will wear out during machining, and a wear-out device used in product manufacturing would result in a defective product. A defective product would result in scrap and rework. This would add up to the cost of manufacturing. This would also result in delays in delivering the product to the customer. Hence, this would result in customer dissatisfaction and subsequently result in loss of reputation of the company in front of the customer. Thus, proper maintenance of the cutting tool would reduce the total maintenance cost.

Many researchers have started using machine learning techniques for classifying the condition of the tool. A tool will be organized into a good tool or a defective tool. One researcher used discriminant analysis for the condition monitoring of the machine tool.

Multiple approaches can make cutting tool condition monitoring. Direct methods include optical, electrical resistance, and Vision systems. The main problem with the natural processes is accessing the wear region's actual area. Benefits would consist of monitoring the wear region and giving indications regarding the cutting tool's essential wear. During machining, accessing the exact part of wear becomes problematic in the presence of coolants and cutting fluids.

In indirect tool wear measurement, specific parameters (e.g., cutting force (Muhammad Rizal 2013), temperature (Muhammad Rizal 2013). Vibrations (Dimla 2000), power (Alonso 2008), acoustic emission (Marinescu 2008, Ren 2014) can be measured, which has a good correlation with the tool wear. Sensors are predominantly used for measuring the condition of the cutting tool (Dimla 2000, Boutros 2011, and Siddhapura 2013).

A typical tool condition monitoring system would consist of sensors used to collect data such as cutting force, power, etc., about the machining process. The data is further processed for extracting features about the signal. In the next step, the tool wear would be assessed using pattern recognition, fuzzy logic, etc. Exercising control based on the output forms the last step in a condition monitoring system.

2.1.1. Cutting Force:

As the tool wears out, it is well known that it would increase cutting forces during the machine. Thus, measuring the cutting pressure would give the degree of tool wear during manufacturing. Dimla (2000) proposed an online tool wear measurement in turning operation. They measured the cutting forces in three directions (X, Y, and Z) during the height. They had used a tool force dynamometer. They used time series and Fourier Transform analysis. One research work (Sikdar 2002) showed the relationship between tool wear and cutting forces.

2.1.2. Acoustic emission:

Acoustic emission (AE) would result whenever the work material undergoes plastic deformation due to the digging action of the cutting tool during machining (Li 2002). Acoustic emission would travel in the material as a stress wave (Li 2002) due to the spontaneous discharge of strain energy. Friction between the tool work interface and phase transformation are other reasons for releasing acoustic waves (Li 2002). They have also demonstrated that the AE signal frequency is much higher than that of the vibration frequency of machines. Thus, AE provides a convenient mechanism for monitoring tool wear. One research (Kakade 1994) demonstrated a correlation between AE parameters such as rise time, ring down count, event duration, and frequency increase with tool wear. Thus, tool wear can be monitored by using an AE signal.

2.1.3. Vibration:

Researchers have used a sensing element called an Accelerometer to measure the cutting tool's vibration. Machining with less vibration would result in quality on the machined component (Teti 2010). One researcher has studied the vibration signal from a drilling process. He could estimate the tool wear of a twist drill (Aliustaoglu 2009).

2.1.4. Temperature:

The temperature developed during machining is directly proportional to the tool wear. Higher tool wear would result in high temperatures during machining. One research has demonstrated using a thermocouple for sensing the temperature between the tool and the workpiece (Kulkarni 2014). The research concluded that the temperature generated during machining would significantly affect tool wear.

2.1.5. Vision system:

Many researchers have used a machine vision-based approach for assessing the tool wear in turning operation (Soham Mehta 2019). In this method, authors have studied the turning process. They have measured the tool wear of a turning tool using the Vision system. They validated their result by using a tool maker's microscope during the measurement.

2.1.6. Surface Roughness:

Kiran (2021) measured the surface roughness of EDM components using a Vision system. During measurement, the vision roughness was evaluated and then compared with the results obtained from the stylus instrument. An excellent correlation was reported as the roughness produced on a machined component depends upon the tool wear of the cutting tool. By measuring surface roughness, tool wear can be assessed. Figure 1 shows the distribution of technical papers in 2021.

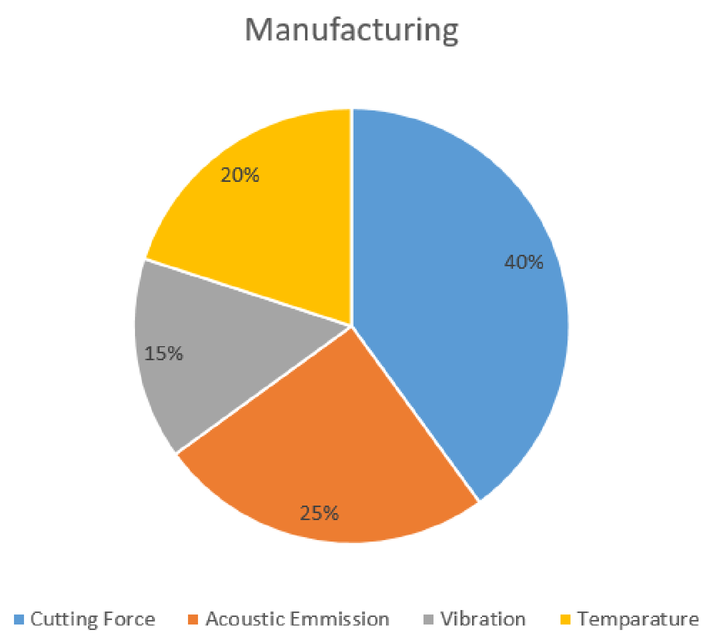

Figure 1 Distribution of technical papers in 2021

2.1.7. Machine learning methods:

With the advent of Industry 4.0, Reinforcement learning (RL) is successfully applied to maintain machine tools (Fitouhi 2017, Wang 2016, and Karamatsoukis 2010). In this method, known transitional probabilities are between states and are confined to two machines and one buffer problem. The main limitation of this method is that it cannot be applied to determine the transitional probabilities of large systems. In the case of large systems, the technique becomes impractical. One research work demonstrated that this model-based RL method would yield better results when compared to the traditional maintenance models (Huang 2019) while estimating the useful remaining service life of a machine tool.

One research work reported using the Multi-Agent Reinforcement Learning method (Jianyu Su 2022) for preventive maintenance. Jianyu Su (2022) have studied preventive maintenance of manufacturing system by using deep learning technique. There will be interactions between the agent and its environment (Huang 2020). Thus the multi-agent reinforcement learning technique to calculate the optimum maintenance policies.

Many of the above techniques described earlier have certain particulars. The first assumption is that the maintenance approach would restore a system's initial health. The second assumption is that many of the above models assume a maximum of six machines and five buffer systems (Huang 2020). In this model, a manufacturing system comprises multiple cooperating agents capable of decision-making at the agent (Jianyu Su 2022). To overcome the limitations of RL based model, the MARL model was proposed (Jianyu Su 2022). MARL model ensures that individual machines collaborate to achieve the manufacturing line's common objective. The method also has the advantage of edge computing, so policy implementation is possible in real-time. Thus, in this model, individual machines in the manufacturing line can take the maintenance policy decision and collaborate with other machines to achieve the common goal.

2.2 Electricity Power Grids

The reliability of power gids is critical. The reliability assessment would help plan, operate, and maintain power grids. Reliability assessment of Generators would help know whether the Generator can meet the demand expectations set by the end-users. Whenever a power Generator fails, it is the responsibility of the Grid management to see that the power distribution is not interrupted. This is possible by using an emergency reserve. Few researchers have proposed intelligent search methods for estimating the reliability of electricity grids (Green 2010, Zhao 2010). These techniques consist of two steps. In the first step, genetic algorithm (Green 2010), modified Genetic algorithm (Zhao 2010), state-space pruning (Singh 1997, Mitra 1999), and particle swarm optimization (Mitra 2010, Benidris 2013) methods are used to reduce state space size. The second step computes the reliability metrics by performing Monte Carlo simulation methods in the reduced state space. One researcher (Gonzlez-Fernndez 2013) proposed a scheme using cross-entropy optimization, requiring few samples to evaluate the reliability-related metrics. One researcher proposed a plan for quickly computing reliability indices of distributed power systems using the machine learning approach (Liu 2017). One method uses the support vector method to assess reliability indices (Pindoriya 2011). The technique uses optimal power flow (OPF) in the reliability evaluation. Using regression quickly calculates probability frequency energy indices of distribution Grids. In this method, OPF will be performed both on training and test samples. In power systems, loss load of probability (LOLP) is an index used to assess the reliability of power grids. This information is helpful for long-term planning. One research work (Urgun 2020) reported using a multi-label K nearest neighbor classification scheme to evaluate the LOLP index, using OPF for training samples. A research study has used group-based data handling classification and MCS to compute the dependability of power grids (Urgun 2020).
The following are the reliability assessment parameters used in the literature.

1. Expected Demand Not Served (EDNS): measures the extent of load shedding (LS) because of system failure to meet the demand. Equation (1) gives the formula for computing EDNS (Kamruzzaman 2022).

$$EDNS = \frac{1}{\mathrm{Ns}} \sum_{s=1}^{Ns} ys \tag{1}$$

In Equation (1), Ns: MCS samples and Ys: the predicted LS f=> s; by trained CNN.

2. Loss of Load Probability Index (LOLP): measures the probability of system failure (Kamruzzaman 2022).

$$LOLP = \frac{1}{\mathrm{Ns}} \sum_{s=1}^{Ns} Lk \quad Lk = \begin{cases} 0, & ys = 0 \\ 1, & ys > 0 \end{cases} \tag{2}$$

In this method, 1: failure state of the system and 0: success state.

3. Load Frequency and Loss of Load Duration (LOLF): measures how often a power system fails (Kamruzzaman 2022).

$$LOLF = \frac{1}{\mathrm{Ns}} \sum_{s=1}^{Ns} \varphi s \tag{3}$$

$$\varphi s = \begin{cases} \sum_{i=1}^{N} \left(\lambda_i^{+} - \lambda_i^{\pm}\right), & if\ ys > 0 \\ 0, & ys = 0 \end{cases} \tag{4}$$

Reliability indices computational algorithm use coefficient of variance as a convergence criterion.
The coefficient of variation (β) is defined as follows (Kamruzzaman 2022).

$$\beta = \frac{\sqrt{Var(RI)}}{\mathrm{E\ (RI)}} \tag{5}$$

Where β is the co-efficient of variation of a reliability index, RI is the reliability index. The algorithm will stop the iteration when the value of β reaches a prescribed value of σ.

3. Conclusion

To summarize, the maintenance function would extend the useful life of a machine tool. Different maintenance techniques are being used in industries, depending upon the criticality of the machine tool. Researchers have proposed new approaches to overcome the limitations of the existing maintenance methods. Artificial Intelligence and machine learning has been used by researchers to successfully demonstrate how smart maintenance function can reduce the total maintenance cost.

4. Future Directions:

Many of the models developed for preventive maintenance have been applied in a fictitious company or case study. More research is required in assessing the preventive maintenance of a real company. Many of the models developed so far have been applied in analyzing six machines and six buffer problems. However, a real company will have more devices and buffers. Many of the techniques proposed by researchers were applied in manufacturing and Electrical power distribution systems. Much research is required for developing preventive maintenance policies in other domains.

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