Deep Science Publishing
https://doi.org/10.70593/978-81-988918-6-0_8

Chapter 8: Predictive maintenance techniques for enhancing the lifespan of agri-machinery

8.1. Introduction

Agricultural mechanization has a key role in the growth of agricultural productivity in a country with a larger population like India. Investments in agricultural mechanization are increasing day by day due to the rising wage of labor. Therefore, boosting farm productivity has become increasingly reliant on the use of mechanization, especially in states like Punjab, Haryana, Western Uttar Pradesh, and some southern states as well. Machinery, which serves as an extension of human labor, is undoubtedly a costly investment. Thus, to achieve the maximum output from the artisan's capital and labor investments, it is essential to plan for its maintenance properly (Jardine et al., 2006; Choudhary et al., 2009; Fountas et al., 2015).

The maintenance of machinery refers to the activities needed to maintain equipment in proper working order by performing major repairs, overhauling, modifying, and servicing the machines. These repairs should be planned well in advance to avoid any breakdown during critical operations. Manual scheduling of servicing is often treated as a functional link between MTTR and MTBF. However, it may not always be possible to minimize MTTR to the lowest level or minimize MTBF to the lowest level by proper scheduling. Since agricultural machinery is used for a limited period during a year and with the extended working and economic life of machines, it is essential to see how the service quality may be improved so that the downtime of machines because of servicing can be minimized. Thus, an increase in the quality of servicing will improve the mean time between failure and a reduced downtime will improve the mean time to repair. Both the above factors will increase the effective overall use of machinery which would reduce the agricultural production costs (Kanchev et al., 2011; Tao et al., 2018)

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8.1.1. Purpose and Scope of the Study

Agricultural production is the backbone of a nation's economy. The present-day competitive business environment has driven farmers toward advanced machinery for maximum production while keeping profit margins low. Agriculture plays an important role in the economy of a country. A great amount of capital is being invested to procure systems or modern equipment. Farmers are adopting the application of equipment for different kinds of operations. Agricultural implements can save time and reduce human effort in doing various agricultural operations. However, the work of those machinery and equipment is very tedious for few days in a year. Therefore, the proper maintenance of them is necessary; otherwise, the productive capacity of the machine will go down and finally result in the loss of profit as well as the life of the machine. Due to its intermittent use for few days, the preventive maintenance of these machinery is to be planned either on a periodic basis or on a utilization basis. Therefore, proper maintenance of all the implements is required so that the machine can be utilized efficiently, thereby saving time and money.

The advance technology in cyber physical systems produces huge data. This data can be helpful in identifying the exact cause for the failure of the machine or automated system. Big data techniques such as predictive analytics can utilize such data to predict the remaining useful life at an optimal point in time. This helps the farmer to modify their work schedule for the season. Accordingly, the required number of workers can be engaged to complete the operation within the stipulated period. The discussion includes the various models that were previously used to predict the remaining useful life. It also discusses the possible future direction for researchers in the field of predictive maintenance. This work ends with the discussion of possible big data methods which can be helpful in predicting the remaining useful life of the machine.

8.2. Importance of Agri-Machinery

Agriculture has always been the chief segment of the economy in many countries. Over a time period, there has been a significant increase in the demand for food due to the growth of population. To fulfill this growing demand, there is a need to increase the production levels while utilizing lesser manpower, land and seed resources. Though the extent of cultivable land is almost constant, with the use of proper tools and technologies, the duration of farming processes can be brought down significantly. This will give room for the farmers to carry upon multiple-crops in a given farming duration, thus yielding more profit. In traditional farming, the processes of plowing, sowing, harvesting, etc., are performed by labors manually which is less-efficient as well as time-consuming. The productivity efficiency of these human labors decreases with increase in temperature, humidity, fatigue and physical performance.

With a rapid development in science and technology over the decades, the life of mankind has changed a lot and is now relying more on machines than nature. The invention of machinery is indeed a boon to mankind especially in the field of agriculture. The emergence of agri-machinery has increased the farm-income as the production processes are carried out effectively with reduced time and workforce. Agri-machineries are mechanical devices used in agriculture which complement the farmers in various tasks throughout the farming process. These equipments are designed for specific and specialized functions like tillage, seeding, fertilizing, spraying, weed control, etc. Agri-machinery can perform the intricate work faster and more efficiently as compared to human resources. The specific requirements for farming activities change depending on the type of crop and its development cycle. In the present fast-scheduled world, people seek for faster, smarter and efficient working machines to lessen their human efforts. Keeping pace with these needs, agricultural engineering was established to deal with the design, development and maintenance of proposed devices.

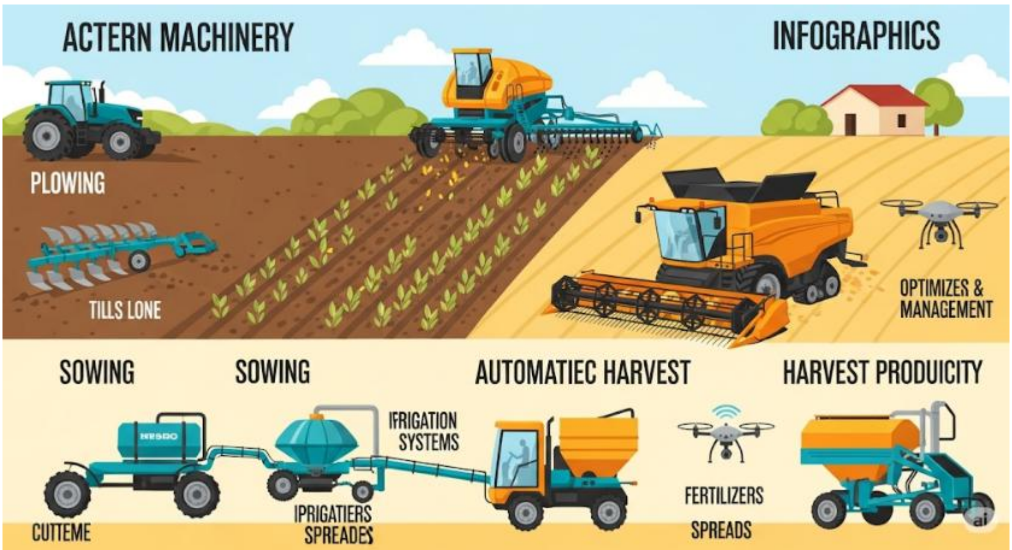

Fig 8 . 1 : The Mechanized Farm

8.2.1. Key Benefits of Agri-Machinery in Modern Farming

Farming is heavily dependent on its operations management support systems and therefore can be considered an industry of great importance authorized to provide food for the evolution of society. Nowadays, as is known, farming is facing many new challenges, such as population growth, changes in people's eating habits, loss of life due to unemployment in rural areas, and so on. To solve these questions, the majority of areas of agriculture are being mechanized in order to lessen the labor force. These areas of agriculture are among the most intense fields of technology with human activity so as to guarantee food security. Mechanization is an indispensable factor in intensive agriculture; however, it is necessary for the development and observance of security standards in the assembly, maintenance, and operation of machinery, as well as for the preventive and corrective maintenance of such equipment.

Agricultural growth in the past hundred years is mostly credited to mechanization. Development and growth of markets have increased the need for faster and better agricultural practices. Activities such as plowing, seeding, fertilizing, crop maintenance, and harvesting are tough to function and due to labor demands, their operation may be at risk. Crop losses from having operations too late demand equipment to enhance crop operation timing. Agri-machinery development and implementation can control operation time and minimize down time from a variety of operations making it the major task preceding automation. During the tilling of the crop, implementing machines can help in the mixing and sterilizing of the soil, as well as the mechanical planting of the crop cycles. For example, during sugarcane planting formulation of vermicompost or bio-pesticides can be integrated in the tilling machines.

8.3. Overview of Predictive Maintenance

Predictive maintenance (PdM) is a proactive maintenance strategy used by manufacturers to monitor the condition of critical equipment installed in their factories and perform maintenance work as required. PdM helps to improve shop floor productivity. This paper attempts to enhance machine life by predictive maintenance techniques. The predictive maintenance strategies are deployed by monitoring equipment parameters such as noise, temperature, vibration, pressure, flow, and electrical energy consumption. Electrical signature analysis is one of the most used predictive maintenance techniques among users. Electrical signature analysis is a well-established tool for diagnosing faults in electrical machines as well as improving machinery lifetimes. It facilitates the study of electrical machine signatures and acts as an information retrieval method to explore the various alterations introduced in the current waveforms by the mechanical, electrical, and thermal faults. Monitoring of current waveforms could improve electrical machine operation.

In the industrial world, the increasing demand for energy efficiency and optimum operation of industrial machines has meant that companies are forced not to overlook any parameters linked to the correct functioning of the machines. In this context, Electrical Signature Analysis can be considered as an absolute non-invasive diagnostic technique capable of successfully analyzing the health of the industrial machines. It involves the study of the electrical signals that an electric machine naturally absorbs during its operation, thus reflecting the influence of all the internal and external variables of the machine. Considering that electric machines are maintained for long operational periods, in the context of the monitoring of their health, the use of advanced statistical tools for the processing of the absorbed electrical data has begun to attract widespread interest. The monitoring of the health of electric machines, through the study of the absorbed data, allows the trend to be followed over time and issues related to its deterioration to be assessed and detected.

8.3.1. Key Principles of Predictive Maintenance

As the name suggests, predictive maintenance techniques use predictive analytics for the execution of maintenance, an optimum technical, financial, and organizational arrangement that aims to improve reliability and reduce costs, both for the owner and technical services. For predictive maintenance to be properly carried out, the following assumptions must be made: models are built and, in general, we will know what indicators we should monitor just for certain types of agricultural equipment; the damage mechanisms to which agricultural machines are subjected due to the wear of certain components are equal to or very similar to those of the rest of the global fleet of the same machines; the damage mechanisms are related to the work requirements and not to the working time; most of the failure modes can be corrected with maintenance actions allowed by the predictive technique; and for a good prediction, enough healthy and damaged records of the technology used are available.

With predictive maintenance, just as with detection-based maintenance, failures will occur during the operation of the machine, which will indicate a greater or lower risk for the use. But as conditions data from the work and machines are available, just as with the first type of maintenance, which has been nicknamed condition monitoring, instantaneous risk estimates can be made earlier and more objectively. This synchronous monitoring also allows us to act immediately and not have to wait for the user or the operation supervisors to detect that something is wrong and request the repair.

8.4. Data Collection Methods

Data-driven models rely on information collected from data sources. Data sources are the collectors of data which are later used for data-driven model prediction and evaluation. Various data collectors can be used to collect various data features. These data sources are broadly classified into two different categories; Sensor and logging devices. Sensor-Based Data Sources are defined as the devices which collect distinct variants of data features. Data features collected using sensor-based data sources include images, vibrations, sounds, temperature, humidity, fuel consumption, hydrocarbons, carbon monoxide, accelerations, engine pressure, etc. During agriculture operations sensors could be allocated to different components of agriculture machinery increased data features collection efficiency.

Sensor-based Data explore a data-driven model design for multiple agriculture machines to detect its failure using data features collected from different sensors at various intervals. They first detected failures on tillage equipment and crop sprayers and developed some maintenance suggestion. They then derived recommendation for the remaining examined equipment and the other major repairs. An approach has been presented to predict the workability, damage potential, and influence on harvesting process performance of some rice harvesters based on hydraulic oil data. Data features proposed to classify multiple damage variables in rice harvesters was for hydraulic oil used in rhizome damage, injector jet, defective guards, and lower header damage. They proposed environmental condition and soil feature-based model for predicting the draft and fuel consumption of rice combine harvester using different fuzzy-based data-driven models. The experimental model was equipped with real-time monitoring data logging techniques for soil moisture content, temperature, humidity, and predicted the draft and fuel consumption of rice harvester operations.

8.4.1. Sensors and IoT Devices

Prediction maintenance is the technique which aims at avoiding any kind of breakdown of mechanical devices by predicting the future behavior using previous data collection and processing. Sensor-based data collection, using information from physical systems, or systems on chip are being seen as a trend that will reshape data collection, real-time analysis and subsequent avoidance activity. IoT systems are able to automatize this task and allow people to approach problems no matter the geographical position where they are located.

The capacity to "connect everything" by integrating sensors in an IoT ecosystem presents the cost effect of incrementing the number of systems in a particular application. The main advantage is the ability to exploit the cloud computing computational capability, able to reduce the cost of dedicated platforms or modulators that implement local analysis. In predictive maintenance, in fact, the health monitoring of the system could be managed by a digital platform that provides, such as additional services, the logic filter for outlier detection and the analysis of the vehicle behavior using machine learning. By sending only data that necessitate to be analyzed from a dedicated service, avoiding critical information for the digital twin creation, is able to increase the RDA.

The analysis of Agri-food systems is able to base the technology in order to create new services, especially for traditional works that is characterized by data hunger. If we look at a precision should be included the carrying out of light or cultural actions that must be detected by a cloud computing protocol that helps to avoid harm to the plants directly in the costs and in the natural products. In the new-generation Planner, we observe the methodology to implement IoT solutions to people and vehicle health, improving the service and making available new information and new interpretative keys to services that have been developing over the years, such as traditional forecasts.

8.4.2. Data Logging Techniques

Data logging, also known as electronic recording or data acquisition, entails capturing and storing data for analysis and record-keeping. It has evolved from simple analog capture devices to more advanced digital devices incorporated into networks of computers, sensors, and probes. Simple data loggers are used extensively in environmental monitoring or experimentation, usually employing multiple sensors and probes in remote locations. Commercial products are also available for online real-time sensing, but these are generally more expensive since they operate using protocols. These environmental data loggers detect temperature, humidity, pressure, light, motion, and acceleration using a variety of sensing technologies such as thermometers, hygrometers, barometers, photodiodes, microwave photonic devices, and MEMS accelerometers.

System design engineers recognize that both acquisition and logging tasks can be accomplished using microprocessors that interface to the sensing elements and incorporate onboard memory storage along with other input and output functions. Such intelligent data loggers can be used in a variety of logging applications such as temperature measurement, event logging, voltage logging, temperature and voltage logging, collision characteristics logging, and time stamp logging, among others. In most configurations, only limited task-specific specialty hardware is required, in addition to the microprocessor. The integrated circuit technology available today makes it possible to add incorporated timing, communication, power management, and control features at component costs that were previously reserved only for high-volume applications. The loading of sophisticated software is often all that is needed to implement the design. What’s more, application circuits can be developed rapidly so that these integrated building blocks can pave the way for the rapid development of more cost-effective solutions for low-volume applications.

8.5. Data Analysis Techniques

Many approaches for predictive maintenance data analyses are covered in the literature. Statistical and machine learning approaches are frequently exploited to analyze the available failure datasets. This section presents a number of these approaches.

General exploratory data analysis bottlenecks in predictive maintenance analysis are often overcome by common statistical methods. Basic descriptive analysis utilizes common sample measurements, such as mean, standard deviation, probability density estimation, etc. However, a visual exploration of the variable distribution provides a more insightful data understanding. Common visual exploration techniques comprise histograms and boxplots. If not just visualized but calculated recursively for multiple timeframes, these statistics provide increasing knowledge on how the condition is changing over time, e.g., over different seasons.

Moreover, point-wise tests, such as the Mann-Kendall test, can be applied to conveniently check for significant monotonic increases or decreases over time. If a variable is tested to be stationary, probability models such as the generalized extreme-value distribution make sense for estimating the time to next failure and its future prediction. These statistical techniques can be employed for sensor signals, too. However, as time series usually exhibit not just seasonality but show autocorrelation, i.e., a dependence between observations of the same variable over time, more advanced techniques are required to model them appropriately. The classical Autoregressive Integrated Moving Average model can be used for stationary and non-stationary time series. More advanced variants allow for multiple seasonalities or the inclusion of explanatory variables, while the current HP filter and Decompose algorithms allow decomposition of nonstationary time series into seasonal, trend, and noise components.

8.5.1. Statistical Analysis

Statistical techniques for analyzing data express deterministic functions and relationships of variance and covariance. Apart from listing some conclusions from the data analysis, a statistical technique examines relationships of the variance and variations of the data. If the data has significant variations, the existing relationships are examined, and if necessary, new deterministic relationships would be developed to consider the existence of relationships or models for these variations. For fault identification, a model of normal operation is developed using statistical prediction or hidden relationships by clustering, and the identified faults are the deviations from the model area. The statistical analysis techniques used to analyze any breakdown data for predictive maintenance are broadly classified into two categories: Data-Sampling Techniques and Data-Modeling Techniques.

Data-Sampling Techniques: Consist of Statistical Process Control, Quantitative Trend Monitoring, Cumulative Sum Control Charting, and Multivariate Statistical Process Control. These techniques identify the fault as any deviation of the sampled unit values, ranges, average or variances of the measured variable, or a linear combination of the values to those areas defined by the preestablished variations for these measures using either the established model or derived relationships. Reduction or increases in any of these sample measures point to a fault in predictive maintenance of machines as they represent a loss of efficiency or capacity area, deterioration of certain areas with set degrees of freedom, and loss of the machine’s functional relationship area.

Data Modeling Techniques: These techniques examine the entire data space by developing probability density functions with model parameter point estimates and their variations of unknown functional relationships or by developing probability density functions of the deterministic model or hidden relationships by clustering. Hidden Relationships by Reviewing Clusters: The probabilistic detection of the model relationship area achieved by any clustering of the data’s equations would enable identification of hidden deterministic relationships in the data.

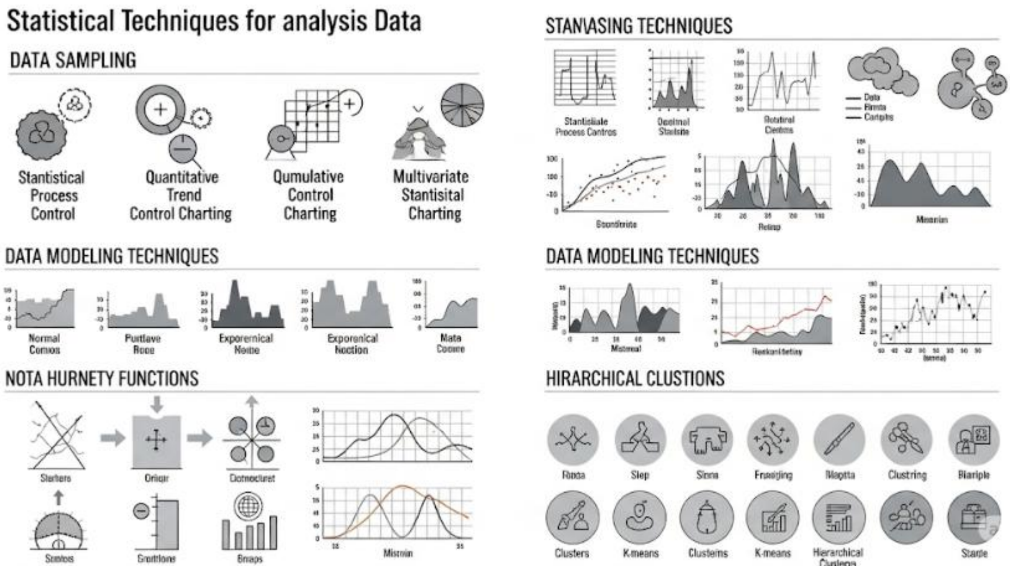

Fig 8 . 2 : Statistical Methods for Data

8.5.2. Machine Learning Approaches

Machine Learning techniques have gained extensive attention in recent years due to the developments in data collection, data storage and the accessibility of enriched research literature. Machine Learning approaches are a subset of Artificial Intelligence and these algorithms learn function mapping inputs to outputs based on the technique and data. Supervised models are able to predict the deviations using feature data collected from different engines and the labelled historical data including failures. The labelled data includes particular fault codes or symptoms such as vibrations, engine oils, run hours when the engines failed. Control based algorithms are able to detect the deviations based on the behaviour of engine parameters during the operations for a certain time duration.

These algorithms detect the abnormal behaviour during its lifetime such as abnormal vibrations, abnormal engine oils, abnormal number of run hours which also leads to low residual characteristics of engines. Unsupervised techniques such as clustering and hidden Markov models are able to classify the engine models or states to group similar types of engines observed from the used engine data and then predict based on the type and states by training a certain state.

Support Vector Machines are supervised learning algorithms which perform classification and regression analysis. The SVM uses a kernel function to create hyper planes in a multidimensional space to separate different classes. SVM have been used for fault diagnosis of bearings in rotating machinery, has been applied for predictive maintenance. However, SVM requires the labelled data for diagnosis. Neural Networks are mainly known for classification and prediction techniques. Neural networks are aimed at the prediction of data set containing input and output data along with weight to minimize the output error. Neural networks for diagnosing faults attributions has been applied for predictive maintenance. However, the application of Neural Networks for many fault symptomatologies using different types of Monte Carlo methods. A three-layered feed forward neural network for metalcutting predictive maintenance predicts the need for maintenance based on a comparison of the predicted and actual levels of performance. However, the training data set is the main concern for the neural networks working in actual production environments.

8.6. Condition Monitoring

The process of proactively testing a machine is known as condition monitoring (CM). CM uses information gathered in real-time to highlight machinery conditions that are outside of their consulted limits. The main purpose is to inform predictive maintenance and protect machines from catastrophic failures by pre-alerting staff about such danger. Several techniques have been developed for CM, but not all of them assess physical phenomena in their foundation: infrared thermography, vibration analysis, ultrasound and laser shaft alignment, electrical parameters, and lubrication condition.

Few techniques are as well-established in the CM field as vibration analysis. It is backed by decades of research that contributed to a better understanding of the link between machinery dynamics and overall conditions. Nowadays, it is not uncommon to apply this technique to detect several types of faults in a single machine. Vibration data is relatively easy to collect, but the difficulties in the analysis process stay mostly in the creation of accurate models of the dynamic response, the understanding of the physics of the dynamically coupled components, and the proper interpretation of the results.

As is the case for other CM techniques, different causes of machinery malfunction may be detected through vibration analysis. Variations in imposed or applied loads by the connected components can cause rotor unbalance, misalignment, bent shaft, broken rotor bars, among other issues that generate a positive work only during the cycle of mechanical impedance or reactive torque. Axis-width changes may suggest a rolling element fault, as do windings conditions that violate continuous symmetry, and stationary drill strays may lead to electromagnetic noise signatures demanding further investigation.

8.6.1. Vibration Analysis

The operation of machines and systems provides certain Input and Output signals. The objective is to differentiate between normal behavior and abnormal behavior. The variation of these parameters over time results in a pattern, which is known as Internal State Measurement. Analysis on changes in patterns can be used to detect the subtle changes in performance long before a malfunction. With the help of internal state measurements, an anomaly is detected and a failure, fault, or worse, a malfunction may be predicted.

Vibration Monitoring is a powerful predictive maintenance technique for many types of machinery. It relies on measuring vibrations transmitted through the flanges of motors, bearings, pumps, turbines, and many other types of rotating and reciprocating equipment. Vibration levels provide a snapshot of machine health at a specific time, and trends indicate the direction and rate of change. If machines are maintained according to their operating performance and actual wear condition, as indicated by the vibration levels, the overall maintenance costs will be significantly reduced. Vibration Monitoring provides a warning that a machine is in trouble, but the actual fault identification and diagnosis usually depends on the skilled interpretation of the vibration data.

Vibration diagnostic techniques are proven to be reliable tools for predicting fatigue and subsequent failure in rotating devices. As a result of the modifications developed, fatigue-failure prediction based on vibration data have become more efficient. Thus, Vibration Monitoring has become accepted practice for monitoring the condition of virtually all types of rotating machinery and is especially suited for the machines and systems which are based on the relationship of input and output, even when the monitoring is being performed from a remote location and may be included in an automatic condition monitoring system.

8.6.2. Thermal Imaging

Thermal imaging, sometimes referred to as infrared thermal imaging or thermography, is a sensor-less camera process that captures emitted infrared energy, or heat, in a picture format, showing temperature variations. It is borne of the observation that all matter above absolute zero emits infrared radiation as a function of its temperature. In a world of motion and change, the thermographic camera sees in the dimension of time, the disease mechanism causing the irregular thermal patterns, and it senses localized changes from normal background thermograms associated with diseases before the onset of any visible changes. Simple because it is less demanding on the user than other techniques, faster than palpation and possibly cheap because of the lack of risk and simplified procedure, the technology is capable of providing information that knit together the appearances, information power and simple application of thermal imaging makes it unique. The brain is an integration center that tries to maintain a constant disparity between the emitted infrared radiation from both sides of the head and adjust the vasomotor tone until balance is achieved.

A thermovision system is a device that creates thermal images using nonionizing infrared radiation. Such radiant heat is invisible to the naked eye, but it can be registered as a function of its intensity with special sensors that are electrically or mechanically scanned or are unscanned. The electronic scanning-type attributes a thermal image by sensing and processing the radiant response of thousands of little, infrared-sensitive, heat-sensing elements. Such devices have the ability to scan and detect very subtle temperature differences within a given infrared field of view and can provide real-time images. The radiated energy is detected by numerous detectors in the sensor array, which respond to differential temperature changes within the region of interest and the response is processed into an image format, with hues or colors mapped to specific temperature levels.

8.7. Predictive Maintenance Models

The majority of the existing PdM literature consists of predictive maintenance models. They are developed to detect equipment failure before it occurs. Roughly, predictive maintenance models can be categorized into two sub-categories. The first category consists of models that predict a failure time point. The second category consists of models that predict the remaining useful life. Predictive maintenance models can rely on either condition or performance monitoring data, or a combination of condition and performance monitoring data and historical data to predict failure events. Condition monitoring data usually consists of physical and/or chemical signals, while performance monitoring data usually consists of system performance levels and pressure or power consumption.

Failure Prediction Models. An example of a failure prediction model, using just condition data, is a hidden Markov model, which has been augmented with hazard rate functions corresponding to each hidden state and with an assumption of Poisson-distributed remaining times-to-fail. Models like those, while simple to formulate and run, will provide predictions that may not be realistic. They will tend to predict a failure long before one is actually likely to occur. In doing so, such models tend to artificially "flatten" the distribution of predicted remaining times to failure.

Remaining Useful Life Estimation. A more general type of predictive model is one that predicts a condition variable that captures the current health of the machine. This type of predictive model may also use condition monitoring input data; but based on it, the predictive model learns the conditional distribution of a health variable over time. By taking this statistical perspective towards remaining RUL estimation, we are better able to predict remaining useful life at previously unseen time points, as we can take into account the inherent uncertainty and the knowledge of failure time distributions for similar machine faults in the decades of historical records stored on such machines.

8.7.1. Failure Prediction Models

In predictive maintenance, the process of modeling is often understood as relating to the failure state, which is identifying the point or threshold in time at which a failure actually occurs. A common approach is using supervised models which are trained on operational data from machines experiencing failures, and results are presented in form of time-to-failure predictions. However, several disadvantages and difficulties are faced in added value over other remaining useful life or state-of-health based predictive models. Since only limited failure data is available, failures need to be correctly modeled to avoid bias. If failures have different characteristics, the model may not perform well on the remaining types. Markovian models suffer from the problem that the sequencing of transition rates between different degradation states is not known. Moreover, these sequence dynamics may be subject to stochastic perturbations, especially for small state and scale systems. In addition to that, stochastic hidden state estimation methods do not give a direct diagnosis even if the degradation of a model may have passed a warning threshold.

In this section, we are concerned with failure prediction modeling, that is the estimation of failure time points and are then using any machine specific threshold from the prediction score for diagnostic assessments or for remaining life attribution. Most modern machine models fall into this supervised approach. These methods require event or failure labels for specific machines to learn the mapping. They are often formulated as binary or categorical classification problems to predict if, and if so, when a machine will fail, and later on post-process the output score of the classifier to determine the remaining useful life. Intensive not labeling efforts by own or external data-sharing initiatives are required, which are among others under pressure from cybersecurity and patent-sensitive business data. Domains of interest for RUL modeling include CNC, milling, generic industrial robotics, and plant machinery.

8.7.2. Remaining Useful Life Estimation

Remaining useful life (RUL) estimation is another model for predictive maintenance. RUL estimation is used in applications where RUL prediction is a critical need, such as condition-based maintenance where an asset is taken offline prior to or just at failure. In some cases, RUL prediction is not only an important aspect of maintenance activities, but also a design consideration. In these applications, if a design undergoes a certain amount of degradation during its use, the phase of use can provide important information to users or buyers. The business domain provides contracts and obligations for products and assets, and the idea is quite similar to the RUL prediction. Based on contracts, these types of predictions can easily generate possible penalties or lost revenue as a result of turning off a machine. Yet, such predictions can directly impact operations when an asset is operated above the limits.

Most of the existing fault prediction or fault classification approaches need a clear decision. If the model predicts a fault at day t1, reclaiming the asset five days before the predicted fault is very costly for the operation of the asset, as it stops the operation and such a reclamation needs to be prepared. Also, any fault prediction needs to be done in advance using a planning stage, as it would be impossible to work on the asset and wait for a failure to collapse. If the determination of no fault is used as a decisive criteria, more advanced decision criteria could be applied. One option is costs associated with a wrong decision that relies on engineering reasons as the costs of estimating no failure six days before failure need to be higher than predicting a fault as such. In recent years, a lot of research has been put into the prediction of condition monitoring. Still, it fails to translate condition monitoring predictions to RUL predictions.

8.8. Implementation Strategies

The successful implementation of predictive maintenance techniques for agri-machinery requires careful integration with existing systems and processes. This includes ensuring that the predictive maintenance tools selected are compatible with existing data acquisition and analysis systems. In many cases, companies are already collecting high-quality work order data, but this data must be processed, analyzed, and interpreted in order to be used as a predictive maintenance strategy. Additionally, existing infrastructure may add complexity to predictive maintenance models. For example, if some but not all machines are equipped with sensors then a hybrid predictive maintenance system must be developed that combines deterministic and probabilistic models in a way that utilizes available sensor data while still accounting for uncertainty about the condition of non-sensor machines.

Each of these steps requires expertise in machine learning algorithms as well as an understanding of the business, its domain, and its decisions. This expertise may be internal or external, and usually a combination of both. It is advantageous for any maintenance department to develop and deploy predictive maintenance techniques in partnership with algorithms experts; data and domain expertise should overlap since the data is from specific maintenance activities. In addition to analyzing existing work order data, consideration should be made to capture more–if possible–to develop confidence in a predictive maintenance strategy. This may mean more intensive data collection efforts in the short term with the goal of longer-term efficiency gains once a predictive maintenance program is in place.

8.8.1. Integration with Existing Systems

The implementation strategy will be different, as there are different types of Agri-Machinery manufactured by different manufacturers carrying different equipment used to help the farmer in its social and economic progress. The manufacturers will have to see how and what is to be integrated into the existing hardware, to make the system usable. Like for example, the Cutter Header used in a combine harvester is made in different designs and types. The integration of load sensors, flex sensors, edge sensors, etc. is attainable in some of the designs, to be able to track the condition of that component. But some designs do not have enough space to accommodate the proposed sensors. Supporting infrastructure also needs to be developed for each component. The Agri-Machinery are used in the fields for farming, the environment is harsh for the wiring, and connectors used for supporting the component data transfer. Repeated shocks and vibrations play in degrading the integrity of the system. Data from each of the addressed sensor systems needs to be transferred to data loggers, and connected to the Bluetooth module. The data will be transferred and accessed by the user on his personal mobile via the application. The design will be an upgrade of the existing control and monitor systems, which makes it cost-efficient and economically viable for the user. The technology is an upgrade of the existing models, providing additional services. The design can also be proposed for multiple sensors to be interfaced at different sites of a subsystem. The proposed and addressed modules can also be integrated into a Smart Cattle Management System, Smart Milk & Seed Production System, Smart Fishery Management System, and Smart Agriculture Management System for maintaining the overall work of the plant and production.

8.8.2. Training and Development

Training and development is one of the most important elements in terminating the barriers of changing organizational culture to achieving successful PD success. Training enables everyone in the organization to update their skills. As the PD strategy involves utilizing advanced tools for the purpose of accurate and timely decision-making, training is needed throughout the organization for both decision-makers and technicians performing technical activities. Employees need to shift from autonomous working to collaboration. A PD strategy stands for shared decision-making along the asset management planning, that is, maintenance, production, projects, and financing specialists should obtain insights into the other specialists' areas and the impact of their decision on the overall performance of the enterprise. The members of the maintenance team typically have varied and in-depth experience of the technical status of the individual components and systems but decision-making requires information about the cost incurred during production. Decision-makers from the production should be educated in using accurate and timely information on the technical performance of the production assets to increase both efficiency and effectiveness.

Training serves as a mean to uplift the overall competence and skills of the workforce in order to complete the technological pioneering barrier. Organizations should not only be interested in external training but focus on developing internal training due to the tacit knowledge of the experienced employees. Employees need to understand the principles of predictive maintenance and the importance of educating the development and training budget. The enterprise should broaden its perspectives and involve various external companies and organizations in order to further develop its pedagogical approach.

8.9. Conclusion

The future of the agricultural industry is being transformed by advances in big data, cloud computing, the Internet of Things (IoT), and machine learning. The use of cutting-edge technology and smart agriculture can help save money, time, labor, resources, and the environment. The adoption of state-of-the-art sensor-based systems in agriculture machinery can be used for predictive maintenance to ensure enough uptime and fuel efficiency of the machinery and reduce its operational costs. In this brief communication, we presented recent developments in the predictive modeling of operation status (working, idle, and abnormal status), fuel consumption modeling, and condition monitoring of agriculture machines based on the signals of sensors/actuators of machines implemented in study tasks as well as other intelligent agriculture technology systems currently available. This past research lays a solid foundation for the future development of smart agriculture using these sensor-data-based predictive maintenance systems, which can be carried out across a wide variety of agricultural tasks, agriculture machines, and other autonomous robotic systems, such as drones, automated ground vehicles, and automated harvesting robots.

In the future, research on sensor-data-based predictive maintenance for agricultural systems should expand beyond predictive modeling of fuel consumption and operation status into more predictive maintenance subjects, including real-time condition monitoring, predictive modeling of wear, reliability, and other performance characteristics of different kinds of agricultural systems, and predictive maintenance of autonomous robotics systems so that precision agriculture can realize the ultimate goal of high-quality, high-efficient, low-cost, sustainable development of agricultural industry, alleviating the shortage of agricultural workers in the world, especially in developed countries.

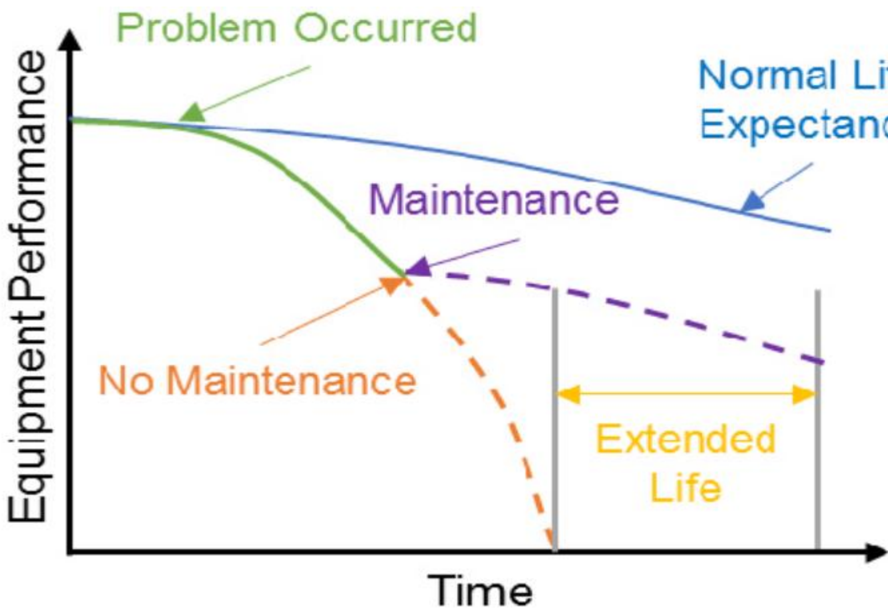

Fig 8 . 3 : Predictive Maintenance Techniques

8.9.1. Summary of Findings and Future Directions

In all, the work has shown that predictive maintenance plays a viable and inevitable role for managing the repair/replacement actions in Agri-Machinery. The study has presented the crucial research links as well as future work directions in several aspects of predictive maintenance while also presenting the challenges of Adaptive intelligent techniques in the Agri-Machinery domain. Though the work has shown the applicability of the concepts in a larger vision of pioneering intelligent Agri-Machinery to be pointlessly driven and embedded with wireless gadgets, false alarm due to false triggering of events need not to be ruled out. The concepts used in getting early response could be modified as per the Critical Value Charts which may trigger an alert if values fluctuates within the radius of Red Alert Value. Real time availability of spare parts and considering hidden costs may lead an Agri-Machinery owner strongly adherent towards predictive maintenance policy. Furthermore, addition of miniaturized, wireless embedded smart gadgets to machines may guide the controlling systems to opt for switching action without human interference. But, severity measure concepts although contrary to the opinion that costs are to be down played in intelligent machinery policy may help in optimizing the uncertainty costs.

Current scenario depicts that researchers have purely visualized the location of Agri-Machinery applications with manifold works done in a vertical manner. Application and prediction of controllable Agri-Machinery based on machine as well as economic parameters in multi facet directions has still remained untouched from a horizontal point of view. Stochastic modeling for networking of Agri-Machinery which also involves human variable for logistic planning during peak seasons is still a debatable issue to implement. Hence, an earnest appeal is made in respect of consideration of stochastic modeling of logistics in a collaborative way by both engineer and field personnel to work in tandem for future research work.

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