

# A review of maintenance management of tractors and agricultural machinery: preventive maintenance systems

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**Abstract:** Agricultural machinery maintenance has a crucial role for successful agricultural production. It aims at guaranteeing the safety of operations and availability of machines and related equipment for cultivation operation. Moreover, it is one major cost for agriculture operations. Thus, the increased competition in agricultural production demands maintenance improvement, aiming at the reduction of maintenance expenditures while keeping the safety of operations. This issue is addressed by the methodology presented in this paper. So, the aim of this paper was to give brief introduction to various preventive maintenance systems specially condition-based maintenance (CBM) techniques, selection of condition monitoring techniques and understanding of condition monitoring (CM) intervals, advancement in CBM, standardization of CBM system, CBM approach on agricultural machinery, advantages and disadvantages of CBM. The first step of the methodology consists of concept condition monitoring approach for the equipment preventive maintenance; its purpose is the identification of state-of-the-art in the CM of agricultural machinery, describing the different maintenance strategies, CM techniques and methods. The second step builds the signal processing procedure for extracting information relevant to targeted failure modes.

**Keywords:** agricultural machinery, fault detection, fault diagnosis, signal processing, maintenance management

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## 1 Introduction

Preventive maintenance is an extensive term that consists of a set of activities to improve the overall reliability and availability of a system (Tasi et al., 2001). All kinds of systems, from conveyors to automobiles to overhead agricultural machineries, have prescribed maintenance schedules expressed by the manufacturer that attempts to decrease the risk of system breakdown and total cost of maintaining the system. In general, preventive maintenance activities include inspection, cleaning, lubrication, adjustment, alignment, and/or replacement of sub-systems and sub-components that are

fatigued. Preventive maintenance activities can be classified in one of two ways, component maintenance and component replacement (Khodabakhshian and Shakeri, 2011). Maintaining suitable air pressure in the tires of a tractor and replacing them with new ones due to weariness can be mentioned as an example. Noticeably, preventive maintenance involves a basic trade-off between the costs of conducting maintenance and replacement activities and the cost savings attained by minimizing the overall rate of happening of system failures. Designers of preventive maintenance schedules must weigh these individual costs in an attempt to minimize the overall cost of system operation. They may also be interested in maximizing the system reliability, subject to some sort of budgetary constraint.

The introduction of system control has a prominent role in the world of agricultural technology. In the past, different processes of agriculture related to agricultural

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machinery were controlled by human operators, but now an automatic manner by low and high level system control is used (Coen et al., 2007; Coen et al., 2008; Craessaerts et al., 2012). At a managerial level, human operators still observe the process in order to detect process faults, unusual events and/or sensor failures which can disturb the actions of the controllers and cause severe damage to the whole process. However, this managerial task becomes increasingly difficult for agricultural machinery operators due to the ever increasing workload and machine complexity they have to deal with (Rohani et al., 2011). One of the next challenges for control engineers involved with the automation of agricultural machinery will be the automation of fault detection and diagnosis to further lighten the job of the operator.

The idea of this paper is to represent an overview on the applicability of various maintenance strategies to condition monitoring of agricultural machinery, reviews the techniques available and methods in the literature. Up till now, most of these techniques have been applied in system control because of the critical safety norms these systems deal with. It will be shown that fault diagnostic systems have not been given much attention yet in agricultural machinery research. However, these techniques could be of high value at a managerial control level for agricultural machinery.

## 2 Maintenance strategies

Maintenance is needed to ensure that the components carry on the purposes for which they were designed. The basic objectives of the maintenance activity are to deploy the minimum resources required to make sure that components perform their intended purposes properly, to ensure system reliability and to recover from breakdowns (Knezevic, 1993). As is shown in Figure 1, the overall maintenance strategy consists of the supporting programs. Broadly, the strategy consists of preventive and corrective maintenance programs.

## 3 Maintenance elements

As was stated, classical theory sees maintenance as either corrective or preventive. The corrective (also

known as unscheduled or failure based maintenance) is carried out when agricultural machinery stop working or

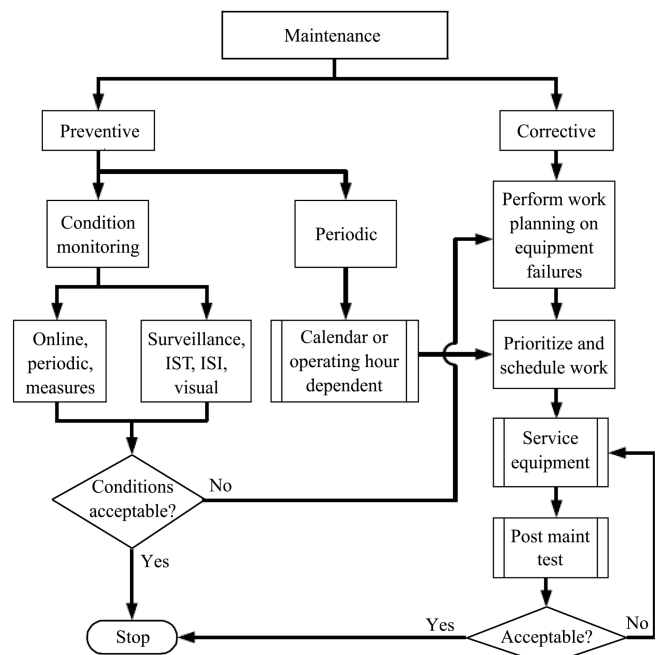


Figure 1 Maintenance strategy

failures occur in any of the components. Immediate replacement of parts may be necessary and unscheduled downtime will result (Ben-Daya and Duffuaa, 2009). So, corrective maintenance is the costly strategy and agricultural machinery operators will hope to resort to it as little as possible.

By contrast, the objective behind preventive maintenance (PM) is to either repair or replace components before they fail (Ben-Daya and Duffuaa, 2009). As is shown in Figure 1, preventive maintenance includes periodic and condition-based maintenance. Periodic maintenance may be done at calendar intervals, after a specified number of operating cycles, or a certain number of operating hours. These intervals are established based on manufacturers' recommendations, utility and industry operating experiences. But decreasing breakdowns in this way comes at the cost of completing maintenance tasks more regularly than absolutely necessary and not exhausting the full life of the various components already in service. An alternative is to lessen against major component breakdown and system failure with condition-based maintenance (CBM) (Pedregal et al., 2009).

CBM process requires technologies, people skills, and

communication to integrate all equipment condition data available, such as diagnostic and performance data; maintenance histories; operator logs; and design data, to make timely decisions about the maintenance requirements of major/critical equipment. So, this involves acquisition, processing, analysis and interpretation of data and selection of optimal maintenance actions and is achieved using condition monitoring systems (Campbell and Jardine, 2001; Marquez, 2006; Marquez, 2010). Khodabakhshian et al. (2009) have demonstrated the applicability of CBM to agricultural machinery, and Khodabakhshian et al. (2008) also have evaluated its cost effectiveness when applied to agricultural machinery. CBM is now the most widely employed strategy in agricultural machinery.

#### **4 Reliability-centered maintenance**

The state-of-the-art method of deciding upon maintenance strategy in the agricultural machinery is reliability centered maintenance (RCM), which has been formally defined as “a process used to determine the maintenance requirements of any physical asset in its operating context” (Moubray, 1993). Briefly, it is a top-down approach that begins with establishing system boundaries and developing a critical equipment list with involving maintaining system functions, identifying failure modes, prioritizing functions, identifying PM requirements and selecting the most appropriate maintenance tasks with the objective of managing system failure risk effectively (Smith, 1993; Deshpande and Modak, 2002). RCM has been recognized and accepted in many industrial fields, such as steel plants (Deshpande and Modak, 2002), railway networks (Marquez et al., 2003), ship maintenance and other industries (Deshpande and Modak, 2002). Of course, any scientific papers about using RCM in the agricultural machinery have not published until now.

#### **5 Condition monitoring of agricultural machinery**

Agricultural machinery, like tillage equipments, planting machines, cultivation machines, plant thinning machines, fertilizing machines, agricultural sprayers, combine harvesters and baling machines have to cope

with time and place-specific conditions. This explains the time-variant character of these systems. A change in crop variety, crop moisture, field slope, temperature, etc., may result in a different process characteristic. On the basis that a “significant change is indicative of a developing failure” (Wiggelinkhuizen, 2007), condition monitoring systems (CMS) comprise combinations of sensors and signal processing equipment that provide continuous indications of component condition based on techniques including vibration monitoring, acoustics analysis, oil analysis, tribology, thermography, process parameter monitoring, visual inspections and other nondestructive testing techniques (Knezevic, 1993).

On the other hand, a lot of process data is available since the recent generation of agricultural machines is equipped with a wide range of sensors and actuators to monitor the different sub-processes. As a result, operators of agricultural machinery used to monitor the status of critical operating major components including fuel systems (such as injection pumps, filters, fuel lines), transmission power systems (such as motors, gearbox, clutches, differential), feeding systems (such as pressure units), handling systems (such as main bearings), safety systems (such as shearing pins and bolts) and cutting systems (such as blades, pivots). Finally, with good data acquisition and appropriate signal processing, faults can thus be detected while components are operational and appropriate actions can be planned in time to prevent damage or failure of components. Performing maintenance properly and following manufacturer's instructions will not only decrease the cost of operation and maintenance but also result in increased reliability, availability, maintainability and safety (RAMS). Some of current techniques are explained as follows.

##### **5.1 Temperature measurement**

Temperature measurement (e.g., temperature-indicating paint, thermography) helps detect potential failures related to a temperature change in equipment. Measured temperature changes can indicate problems such as excessive mechanical friction (e.g., faulty bearings, inadequate lubrication), degraded heat transfer (e.g., fouling in a heat exchanger) and poor electrical connections (e.g., loose, corroded or oxidized

connections). Table 1 outlines the more common types of measurement with comments on a brief technical description of the method.

**Table 1 Thermal measurement methods**

Method	Description
Point temperature	Usually a thermocouple or RTD
Area Pyrometer	Measures the emitted IR radiation from a surface
Temperature Paint	Chemical indicators calibrated to change color at a specific temperature
Thermography	Hand held still or video camera sensitive to emitted IR

Temperature measurement is often used for monitoring electronic and electric components and identifying failure (Smith, 1978). Many tractors and harvesters are now equipped with electronic devices and computers for efficient operation. Of course, temperature measurement can be employed for the structural evaluation of mechanical items of agricultural machinery such as pumps, gears, clutches, bearings, belts, blades, pressure accumulators, conveyors etc but due to the bulky equipment involved this is not a standard methodology amongst agricultural machinery.

## 5.2 Dynamic monitoring

Dynamic monitoring (e.g., spectrum analysis, shock pulse analysis) involves measuring and analyzing energy emitted from mechanical equipment in the form of waves such as vibration, pulses and acoustic effects. Measured changes in the vibration characteristics from equipment can indicate problems such as wear, imbalance, misalignment and damage. Table 2 outlines the more common types of measurement with comments on a brief technical description of the method.

**Table 2 Summary of dynamic monitoring methods**

Method	Description
ISO Filtered Velocity	2Hz – 1kHz filtered velocity
Shock Pulse Method (SPM)	Carpet and Peak related to the demodulation of a sensor resonance around 30 kHz
Acoustic Emission	Distress demodulates a 100 kHz carrier which is sensitive to stress waves
Vibration Meters 4-20 mA sensors	Combine velocity, bearing and acceleration techniques Filtered data converted to DCS/PLC compatible signal

Dynamic monitoring continues to be the one of the most popular technologies employed in agricultural machinery, especially for those that have rotating action (such as rotavator, cultivator, broadcast seeder, fertilizer

spreader, baler, chopper, mower, rake), cabin vibration, engine vibration and vibration produced by agricultural machinery with flexible parts (such as agricultural sprayers) (Hostens and Ramon, 2003; Anthonis et al., 2003; Scarlett et al., 2007; Tint et al., 2012). As for applications, it is appropriate for monitoring the gearbox (Miller et al., 1999; Heidarbeigi et al., 2009 Heidarbeigi et al., 2010) and the bearings (Igarashi and Hamada, 1982; Sun and Tang, 2002). Tandon and Nakra (1992) presented a detailed review of the different vibration and acoustic methods, such as vibration measurements in the time and frequency domains, sound measurements, the shock pulse method and the acoustic emission technique for CM of rolling bearings.

The primary sources of Acoustic Emission (AE) in agricultural machinery are the generation and propagation of cracks, and the technique has been found to detect some faults earlier than others such as vibration analysis (Yoshioka, 1992; Yoshioka and Takeda, 1994; Tandon et al., 1999). Generally, it is possible to judge an agricultural machinery loading level by listening to the noises it makes. This speculative research develops techniques to interpret acoustic emissions from agricultural machinery, for use in a feedback control system to optimize machine field performance. In addition, the application of AE for the detection of bearing failures has been presented by researchers (Tan, 1990). Non-destructive testing techniques using acoustic waves to improve the safety of tractors and balers are presented by Scarlett et al. (2001).

Ball and roller bearings are among the most common and important elements in rotating agricultural machinery and tractors. When a bearing does fail, the secondary damage to associated machine parts and the loss of production greatly exceeds the cost of replacing the bearing. Replacing bearings after a set number of hours is also risky since good bearings are thrown out needlessly and unscheduled failure can still result. The best solution then is to systematically monitor bearing condition and schedule replacement at times least influencing production efficiency. Several methods are currently used to monitor bearing condition. The most common is Shock Pulse Method, also known as SPM,

that is a patented technique for using signals from rotating rolling bearings as the basis for efficient condition monitoring of machines and works by detecting the mechanical shocks that are generated when a ball or roller in a bearing comes in contact with a damaged area of raceway or with debris (Butler, 1973).

### 5.3 Oil analysis

Oil analysis (e.g., ferrography, particle counter testing) can be performed on different types of oils such as lubrication, hydraulic or insulation oils. It can indicate problems such as machine degradation (e.g., wear), oil contamination, improper oil consistency (e.g., incorrect or improper amount of additives) and oil deterioration. On the other hand, whether for the ultimate purpose of guaranteeing oil quality or checking the condition of the various moving parts, oil analysis is mostly executed off-line by taking samples despite on-line sensors having (for years) been available at an acceptable cost for monitoring oil temperature, contamination and moisture (Toms, 1998; Khodabakhshian and Shakeri, 2010). Little or no vibration may be evident while faults are developing, but analysis of the oil can provide early warnings. Generally, to protect your investment, machine condition monitoring based on oil analysis has become an important maintenance practice. Designing an effective oil analysis program will keep important manufacturing assets such as pumps, gears, bearings, compressors, engines, hydraulic systems and other oil-wetted machinery in operation by reducing unexpected failures and costly unscheduled down time. A Condition monitoring of agricultural machinery by oil analysis is presented by Khodabakhshian and Shakeri (2010).

### 5.4 Corrosion monitoring

Corrosion monitoring (e.g., coupon testing, corrometer testing) helps provide an indication of the extent of corrosion, the corrosion rate and the corrosion state (e.g., active or passive corrosion state) of material. Using this technique is very common for monitoring the operation of tillage equipment. The proper adjustment and application of different tools can easily checked observing corrosion areas on tillage tools such as moldboard.

### 5.5 Radiographic inspection and ultrasonic testing

Radiographic inspection and ultrasonic testing are nondestructive tests that involve performing tests to the test subject. Many of the tests can be performed while the equipment is online. Radiographic inspection is a nondestructive testing technique used to evaluate objects and components for signs of flaws which could interfere with their function. X-ray and gamma ray radiographic inspection are the two most common forms of this inspection technique. Radiographic imaging of critical structure of agricultural machinery components due to costly equipments and much time analyzing is rarely used although it does provide useful information regarding the structural condition of the component being inspected.

Ultrasonic testing (UT) techniques are used extensively by the agricultural machinery industry for the structural evaluation of motors, monitoring of rotary components in agricultural machinery and their safety detecting systems. UT is generally employed for the detection and qualitative assessment of surface and subsurface structural defects (Knezevic, 1993; Guo et al., 2001; Endrenyi et al., 2001; Deshpande and Modak, 2002). In ultrasound technique to detect safety of agricultural machinery is presented by Guo et al., (2001) the development of ultrasonic sensors in detecting a moving object around an agricultural machine. Ultrasonically obtained images make it possible to recognize the geometry of defects and to estimate their approximate dimensions.

### 5.6 Electrical testing monitoring

Electrical condition-monitoring techniques involve measuring changes in system properties such as resistance, conductivity, dielectric strength and potential. Some of the problems that these techniques will help detection are electrical insulation deterioration, broken motor rotor bars and a shorted motor stator lamination. CM of electrical equipment of agricultural machinery such as motors, electricity systems of tractors and self propelled machines, generators and accumulators is typically performed using voltage and current analysis. Many researchers demonstrate how the Electrical condition-monitoring is useful for detecting fatigue damage in particular (Seo, 1999; Todoroki and Tanaka,

2002; Matsuzaki and Todoroki, 2006).

### 5.7 Performance monitoring

Monitoring equipment performance is a condition-based maintenance technique that predicts problems by monitoring changes in variables such as pressure, temperature, flow rate, electrical power consumption, capacity and structural components features of agricultural machinery (such as blade angle in tillage implements, tines angle and rotor speed in harvesting machinery, nozzle type and pump performance in agricultural sprayers) can also be used for an assessment of agricultural machinery condition and for the early detection of faults. Many researchers used this technique for agricultural machinery (Sichonany, 2011; Khodabakhshian and Bayati, 2011). Khodabakhshian and Bayati (2011) investigated the effect of machine parameters on hulling performance of pistachio nuts using a centrifugal huller. The hulling efficiency and breakage percent depend on impeller design was considered in their research.

## 6 Sensory signals and signal processing techniques

It is stated that Condition-based Maintenance (CBM) proposed actions based on information obtained through observation and analysis. On the other hand, CM process includes three sub-steps: data acquisition, signal processing, and make a maintenance decision.

Every year, many valuable research papers on CM emerge in thesis, scientific journals, conference proceedings and technical notes (Toms, 1998; Caselitz and Giebhardt, 2003; Müller et al., 2006; Tana et al., 2007; Marquez and Pedregal, 2007; Aradhana, 2009; Wang et al., 2012). In this section, we represent an overview on recent progresses in the diagnostics and prognostics of systems especially for tractors and agricultural machinery. Several models, algorithms, and technologies for signal processing and maintenance decision making will be mentioned below. Finally, the review is concluded with a brief discussion on current practices and possible future trends in CBM.

### 6.1 Data acquisition

The necessary first step in the CBM procedure, data

acquisition, is a process for collecting and storing functional information that emanates from operating physical assets. Two types of data including “event” data and “condition monitoring” data are needed for a CBM program. Event data provides analyzing of some information about special event or happening such as an installation, a breakdown, or an overhaul. Event data also say to us what was done, for example, a minor repair, a preventive maintenance action, an oil change, and so on. CM data consists of observational measurements that we believe are, in some way, related to the deteriorating health or state of the physical asset. CM data can include vibration data, acoustics data, oil analysis data, temperature, pressure, moisture, humidity, and any other physical observations, including visual clues that relate to the condition of an operating physical asset in its environment.

A range of sensors (micro sensors, ultrasonic sensors, acoustic emission sensors, thermographic imagers, etc) have been designed to collect different types of data (Kirianaki et al., 2002; Austerlitz, 2003). Wireless technologies such as bluetooth have provided an alternative to more expensive hard wired data communication. Information systems such as Computerized Maintenance Management Systems (CMMS), Enterprise Resource Planning (ERP) systems, control system historians, and CBM databases have been developed for data storage and handling (Davies and Greenough, 2000). With the rapid development of computer and advanced sensor technologies, data acquisition technologies have become more powerful and less expensive, resulting in exponentially growing databases of CM data. For instance, Mollazade et al. (2009) focused on a problem of vibration-based condition monitoring and fault diagnosis of pumps used in the tractor steering system. With the sensor mounted on the body of gear housing of the pump, vibration signals were measured for various fault conditions by on-line monitoring when tractor was working at a stationary situation.

### 6.2 Signal processing

Data cleaning as a preliminary step of signal processing is needed to perform data acquisition

especially when it is done manually it will include some errors. The probability of error is high for event type of data. Data cleaning is meant to make sure that clean (error-free) data is used for subsequent analysis and modeling. Errors in CM data may be caused by sensor faults, which are handled by sensor fault isolation (Xu and Kwan, 2003). In general, there is no simple, single method to clean data. Sometimes manual examination is required. Graphical tools are helpful in finding and removing data errors. Indeed, data cleaning is indeed a vast subject area.

The next step in signal processing is data analysis. A variety of models, algorithms and tools are available. Their purpose is to analyze data in order to better understand and interpret it. The choice of which model, algorithm, or tool to use for data analysis depends primarily on the type of data collected.

A large variety of signal processing techniques have been developed to analyze and interpret these types of data in agricultural machinery. Their purpose is to extract useful information from the raw signal in order to perform diagnostics and prognostics. Mohammadi et al. (2008) described the suitability of vibration monitoring and analysis techniques to detect defects in applied roller bearings for agricultural machinery. Heidarbeigi et al. (2009) investigated monitoring of Massey Ferguson gearbox in different situation by vibration testing and signal processing. Ebrahimi and Mollazade (2010) presented an intelligent method for fault diagnosis of the starter motor of an agricultural tractor, based on vibration signals and an Adaptive Neuro-Fuzzy Inference System.

### 6.3 Maintenance decision making

The final step of a CBM program is maintenance decision making. Sufficient and efficient decision support will result in maintenance personnel's taking the "right" maintenance actions given the current known information. Jardine (2002) reviewed and compared several commonly used CBM decision strategies. They included trend analysis that is rooted in statistical process control, expert systems, and neural networks. Wang and Sharp (2002) discussed the decision aspect of CBM and reviewed the recent development in modeling CBM decision support.

## 7 Diagnostics

Machine fault diagnostics is a discovery procedure based on mapping information in the measurement features in the feature space to machine faults in the fault space. Detection of a potential failure will result in diagnostic action which is a proactive activity and usually begins with a condition based maintenance process. Traditionally, pattern recognition was a manual exercise, performed with the assistance of graphical tools such as a power spectrum graph, a phase spectrum graph, a cepstrum graph, a spectrogram, a wavelet scalogram, a wavelet phase graph, and so on. However, manual pattern recognition requires expertise in the specific area of the diagnostic application. To provide such skilled personnel is costly and time consuming. Therefore, pattern recognition automatically is highly recommended. The classification of signals based on the type of extracted information and/or features from the signals makes that possible. Many researchers have used machine fault diagnostics in agricultural machinery (Mohammadi et al., 2008; Mollazade et al., 2009; Heidarbeigi et al., 2009; Ebrahimi and Mollazade., 2010; Craessaerts et al., 2010). As an example, Craessaerts et al. (2010) investigated fault diagnostic systems for agricultural machinery. Bagheri et al. (2010) investigated the application of data mining and feature extraction on intelligent fault diagnosis by Artificial Neural Network and k-nearest neighbor for frequency domain vibration signals of the gearbox of MF285 tractor.

In the following sections, different machine fault diagnostic approaches are discussed with emphasis on statistical approaches and artificial intelligent approaches. Machine diagnostics with emphasis on practical issues was discussed in (Williams, 1994). Various topics in fault diagnosis with emphasis on model-based and artificial intelligence approaches were covered by Korbicz, 2004.

### 7.1 Statistical methods

An ordinary technique of fault diagnostics is to detect whether a specific fault is present or not based on the available condition monitoring information without intrusive inspection of the machine. This fault detection

problem can be described as a hypothesis test problem with null hypothesis  $H_0$ : Fault A is present, against alternative hypothesis  $H_1$ : Fault A is not present. In a concrete fault diagnostic problem, hypotheses  $H_0$  and  $H_1$  are interpreted into an expression using specific models or distributions, or the parameters of a specific model or distribution. Test statistics are then constructed to summarize the condition monitoring information so as to be able to decide whether to accept the null hypothesis  $H_0$  or reject it. Many researches have used hypothesis testing for fault diagnosis (Ma and Li, 1995; Kim et al., 2001; Sohn et al., 2002).

A conventional approach, statistical process control (SPC), which was originally developed in a quality control theory, has been well developed and widely used in fault detection and diagnostics. The principle of statistical process control is to measure the deviation of the current signal from a reference signal representing the normal condition to see whether the current signal is within the control limits or not. An example of using SPC for damage detection was discussed in (Fugate et al., 2001). Also, Heidarbeigi et al. (2009) used this method for fault diagnostics Massey Ferguson gearbox by vibration testing and signal processing.

Cluster analysis, as a multivariate statistical analysis method, is a statistical classification approach that groups signals into different fault categories on the basis of the similarity of the characteristics or features they possess. It seeks to minimize within-group variance and maximize between-group variance. Application of cluster analysis in machinery fault diagnosis was discussed in (Skormin et al., 1999; Artes et al., 2003). The hidden Markov model (HMM) can also be used for fault classification. Two recent applications of HMM in fault classification assumed an HMM with hidden states having no physical meaning for two machine conditions (normal and faulty) (Ge et al., 2004; Li et al., 2005). Xu and Ge (2004) presented an intelligent fault diagnosis system based on a hidden Markov model. Ye et al (2002) considered the application of two-dimension HMM based on time-frequency analysis for fault diagnosis. Mohammadi et al. (2008) used this method to describe the suitability of vibration monitoring and analysis

techniques to detect defects in applied roller bearings for agricultural machinery.

## 7.2 Artificial intelligence

Artificial intelligence (AI) techniques have been applied to machine diagnosis more and more and have shown improved performance over conventional approaches. In the literature, two popular AI techniques for machine diagnosis are artificial neural networks (ANN) and expert systems (ES). Other AI techniques include fuzzy logic systems (FLS), fuzzy-neural networks (FNN), neural-fuzzy systems (NFS), and evolutionary algorithms (EA). A review of recent developments in applications of AI techniques for induction machine stator fault diagnostics was given by Siddique et al. (2003). Most applications of fault diagnostic systems in the agricultural industry are found in Artificial intelligence (AI) techniques (Liyang and Youzhang, 2003; Craessaerts et al., 2005; Ebrahimi and Mollazade., 2010; Bagheri et al, 2010; Rohani et al., 2011; Miodragovic et al., 2012). As an example, Ebrahimi and Mollazade (2010) presented an intelligent method for fault diagnosis of the starter motor of an agricultural tractor, based on vibration signals and an Adaptive Neuro-Fuzzy Inference System (ANFIS). In this study, six superior features were fed into an adaptive neuro-fuzzy inference system as input vectors. Performance of the system was validated by applying the testing data set to the trained ANFIS model. According to the result, total classification accuracy was 86.67%. So, they stated that the system has great potential to serve as an intelligent fault diagnosis system in real applications.

In contrast to neural networks, which acquire knowledge by training on observed data with known inputs and outputs, expert systems (ES) utilize domain expert knowledge in a computer program with an automated inference engine to perform reasoning for problem solving. Three main reasoning methods for ES used in the area of machinery diagnostics are rule-based reasoning (Baig and Sayeed, 1998) and model-based reasoning (Araiza et al., 2002). Another reasoning method, negative reasoning, was introduced to mechanical diagnosis by Hall et al (1997). Stanek et al.



(2001) compared case-based and model-based reasoning and proposed to combine them for a lower cost solution to machine condition assessment and diagnosis. Unlike other reasoning methods, negative reasoning deals with negative information, which by its absence or lack of symptoms is indicative of meaningful inferences. Nie and Liu (2007) established an expert system for Farm Machinery Fault Diagnosis based on Neural Network. Bardaie et al. (1988) discussed about the potential usage of expert system in agriculture along with a presentation of the case for the service and maintenance of agriculture tractors.

## 8 Prognostics

Compared with diagnostics, the literature on prognostics is much smaller. Machine prognostic includes two main types of prediction. The most familiar one is the prediction of remaining time before occurrence of a failure indicating current and past/future condition of operating profile of a machine. The time left before observing a failure is usually called "remaining useful life" or RUL. In many situations, especially when a fault or a failure has catastrophic consequences (e.g. nuclear power plant), it is desirable to predict the chance that a machine operates without a fault or a failure up to some future time (for example, the next inspection), given the machine's current condition and its past operational profile. In the general maintenance context, the probability that a machine operates without fault until next inspection interval is a good reference in helping to determine whether or not the inspection interval is appropriate.

Most of the papers in the literature of machine prognostics discuss only the former type of prognostics, namely RUL (Remaining Useful Life) estimation. Only a small number of papers address the second type of prognostics (Araiza et al., 2002; Farrar et al., 2003). In the following sections, it is tried to discuss RUL estimation, prognostics that incorporate maintenance actions or policies, and the determination of the appropriate condition monitoring interval.

### 8.1 Remaining useful life

Remaining useful life (RUL) which is also named as remaining service life, residual life, or remnant life means

remaining time before happening a failure. It is essential to mention that the definition of a failure is crucial to the interpretation of RUL. Yan et al. (2004) employed a logistic regression model to calculate the probability of failure for given condition variables and an ARMA time series model to trend the condition variables for failure prediction. A predetermined level of failure probability was used to estimate the RUL. Ao et al. (2004) described the use reliability of Chinese tractors, as assessed by measuring working hours until failure occurred in an agricultural field.

### 8.2 Prognostics incorporating maintenance policies

The aim of machine prognosis is to provide decision support for maintenance actions. As such, it is natural to include maintenance policies in the consideration of the machine prognostic process. This makes the situation more complicated since extra effort is needed to describe the nature of maintenance policies. Compared to conventional maintenance, mathematical models applicable to the CBM scenario are much smaller (Scarf, 1997). The optimization of the maintenance policies regarding to some main criteria such as risk, cost, reliability and availability is the main idea of prognostics incorporating maintenance policies.

## 9 Condition monitoring interval

Condition monitoring can be divided to continuous and periodic types. Expensive cost and producing large volume of data because of including noise with raw signals are two limitations of continuous monitoring. Periodic monitoring, therefore, is used due to its being more cost effective. Diagnostics from periodic monitoring are often more accurate due to the use of filtered and/or processed the data. Of course, the risk of periodic monitoring is the possibility of missing some failure events that occur between successive inspections (Goldman, 1999).

Christer and Wang (1996) derived a simple model to find the optimal time for next inspection based upon the wear condition obtained up to current inspection. The criterion is to minimize the expected cost per unit time over the time interval between the current inspection and the next inspection time. Okumura (1997) used a delay-time model to obtain the optimal sequential

inspection intervals of a CBM policy for a deteriorating system by minimizing the long-run average cost per unit time. Wang (2003) developed a model for optimal condition monitoring intervals based on the failure delay time concept and the conditional residual time concept. Mohammadi et al. (2011) performed condition monitoring of MF285 and MF399 tractors using engine oil analysis to find the optimum life time of tractor substitution in comparison with the breakdown maintenance method in Iran.

## 10 Conclusion

The basic aim of this paper was to reveal the introducing of preventive maintenance specially condition monitoring system at supporting maintenance management of agricultural machinery. So, the primary focus of this article was reviewing condition monitoring system and application of it to agricultural machinery. Then, recent research and developments in machinery diagnostics and prognostics used in implementing CBM have been summarized. Various techniques, models and algorithms were reviewed. Of the three main steps of a CBM program, namely, data acquisition, signal processing, and maintenance decision making, the latter two were the focus.

There are various techniques for supporting maintenance management each component of agricultural machinery and for all of these techniques there are methods available and were referenced in the literature. The main problems facing the designers of condition monitoring systems for agricultural machinery obviously continue to be:

- 1) selection of the number and type of sensors for data acquisition step;
- 2) selection of effective signal processing methods

associated with the selected sensors;

- 3) design of a sufficient and efficient maintenance decision making.

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## Abbreviation

CBM	Condition based maintenance
CM	Condition monitoring
PM	Preventive maintenance
RCM	Reliability centered maintenance
CMS	Condition monitoring systems
RAMS	Reliability, availability, maintainability and safety
RTD	Resistance temperature detector
IR	Infrared
AE	Acoustic Emission
UT	Ultrasonic testing
CMMS	Computerized Maintenance Management Systems
ERP	Enterprise Resource Planning
SPC	Statistical process control
HMM	Hidden Markov model
AI	Artificial intelligence
ANN	Artificial neural networks
ES	Expert systems
FLS	Fuzzy logic systems
FNN	Fuzzy-neural networks
NFS	Neural-fuzzy systems
ANFIS	Adaptive Neuro-Fuzzy Inference System
RUL	Remaining useful life

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