ECONOMICAL ANALYSIS OF CONDITION BASED MAINTENANCE ON RAILWAY SYSTEMS

by

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ABSTRACT

Maintenance is an inevitable reality in industry. Not only its close relationship with safety but also its direct and indirect costs make it attractive for companies and researchers. For example, Department of Defense (DoD) Maintenance activities in USA consume over $40 billion annually. Maintenance costs at medium-sized power utility companies exceed operating profit.

Initially, the focus for maintenance research was on the periodic maintenance, mainly targeting the identification optimum maintenance period. A new concept of maintenance, in which health of the machine is observed real time and maintenance decisions base on the current and forecasted machine health (Condition Based Maintenance (CBM)), is now under examination with many applied industrial examples

Even though the benefits and value of CBM are irrefutable, is it true to implement CBM in every system? An analysis tool that will evaluate the possible value of CBM considering its investment, setup and management costs is now a great need for industry. It is important for companies to know return on investment (ROI) or internal rate of return (IRR) of CBM system.

It is possible to implement different maintenance strategies for different failure modes in a system since their importance may be different. This thesis presents an

economical analysis model that evaluates the value of CBM for a given system with different failure modes and identifies the optimum maintenance policy for different failure modes in a system. If CBM is identified as the optimum policy for any failure mode, the model reports ROI and IRR.

RAYLI SİSTEMLERDE KOŞUL BAZLI BAKIM SİSTEMLERİNİN EKONOMİK ANALİZİ

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ÖZ

Bakım-onarım sanayide kaçınılmaz bir gerçektir. Bakım-onarım işlemlerinin sistem güvenliğiyle olan direk bağlantısı ve bakım onarım masraflarının işletme maliyetlerinde önemli bir yer tutması gerek araştırmacıların gerekse endüstrinin bakım onarım işlemlerine olan ilgisini arttırmaktadır. Örneğin, ABD savunma bakanlığı bakım faaliyetleri için yılda 40 milyar dolar harcamaktadır. Ayrıca, bakım maliyetleri orta ölçekli şirketlerin işletme karlarından daha fazla olabilmektedir.

İlk başlarda araştırmacıların temel konusu periyodik bakım olup, optimum bakım periyodunun bulunması ve belirlenmesi amaçlanmıştır. Günümüzde ise Koşul-Bazlı Bakım (KBB) sistemleri araştırmacı ve endüstrinin ilgi odağı olmultur. KBB makinanın sağlık durumunu sensörler aracılığıyla topladığı bilgileri analiz ederek sürekli gözlemlemekte ve bu bilgilere göre bakım onarım işlerini en etkin şekilde planlanmasını sağlamaktadır. Ayrıca edinilen bu bilgilere göre ileriye yönelik tahminlerde bulunularak kararlar alınması sağlanmaktadır. Koşul-bazlı bakım yöntemlerine uygulamada çok sık rastlayabiliriz. Örnek olarak nükleer santrali, savunma sanayisi, ulaşım yapılanması ve araba sanayisini verebiliriz.

Koşul bazlı bakım sistemlerinin değeri ve faydaları tartışılmaz bir gerçek olmasına rağmen, bütün sistemler için uygulanması ekonomik açıdan karlı olmayabilir. KBB uygulaması için AR-GE, kurulum ve personel eğitimini içeren ciddi bir yatırım yapılması gerekmektedir. Bu nedenle ekonomik analiz modeli ile bir sisteme KBB uygulamasının fayda analizi endüstrinin ihtiyaç duyduğu bir eksikliktir. Şirketler için bir sistemin kurulumundan once o sistemin yatırım getirisinin hesaplanması önemlidir. Bu tezde sunulan ekonomik model arıza kritikliklerini de göz önünde bulundurarak herbir arıza türü için takip edilmesi gereken en etkin bakım stratejisini (tamir, periyodik bakım veya koşul-bazlı bakım) belirlemeyi amaçlamaktadır. Ayrıca sunulan ekonomik model KBB uygulanması karar verilen arıza türü için yapılacak yatırımın ne zaman kar getireceğini de rapor edilmektedir.

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CHAPTER 1

INTRODUCTION

Maintenance is an inevitable reality in industry. Not only its close relationship with safety but also its direct and indirect costs make it attractive for companies and researchers. For example, Department of Defense (DoD) Maintenance activities in USA consume over $40 billion annually (Fact Book, 2000). Maintenance costs at medium-sized power utility companies exceed operating profit (Baruah et al., 2005). Initially, the focus for maintenance research was on the periodic maintenance (Waeyenbergh et al., 2002), mainly targeting the identification optimum maintenance period. A new concept of maintenance, in which health of the machine is observed real time and maintenance decisions base on the current and forecasted machine health (called Condition Based Maintenance), is now under examination with many applied industrial examples such as military equipments (e.g., aircrafts, helicopters, etc.), power industry, nuclear plants, manufacturing industry, automobiles, transportation infrastructures (e.g., roads, railways, etc.).

Condition Based Maintenance gives insights to perform maintenance actions based on the information gathered through condition monitoring. CBM try to prevent unnecessary maintenance tasks by taking maintenance actions only when there is symptoms of irregular behaviors of a system. When it is established properly and effectively implemented, then it causes significant reduction in maintenance cost by reducing the number of unnecessary scheduled preventive and unscheduled corrective maintenance operations.

Even though CBM leads to many benefits, initial investment cost and possible uncertainties might cause hesitation. A detailed economic analysis of CBM that helps decision makers to analyze the benefits of CBM is needed. An analysis tool that will evaluate the possible value of CBM considering its investment, setup and management costs is now a great need for industry. It is important for companies to know return on investment (ROI) or internal rate of return (IRR) of CBM system, since it requires an initial investment.

Similar study was done by Marquez et al. where they have made an economic analysis of condition based maintenance for railway turnout systems (Marquez et al., 2008). Life cycle cost (LCC) of railway turnouts when condition monitoring is applied was calculated. But, rather than including failure modes and criticality analysis in their calculation, turnout system was considered as a whole and application of CBM for all components and failure modes, was studied in their work. However, the importance and/or criticality of components/failure modes may be different in a system, in which some failure modes may require CBM, some Periodic Maintenance, and even some can go with Corrective Maintenance. In other words, the investment of CBM may not be necessary for some of the failure modes.

On the other hand, Carmignani has developed an economic analysis model that takes FMECA into consideration (Carmignani, 2009). He introduces a model that enables to find the best mix of failure modes to be maintained according to budget constraints. But the cost, which includes maintenance frequency, personnel and material cost, was calculated based on just CM policy .PM and CBM policies were not considered.

Therefore, an economic analysis of CBM taking into consideration also FMECA will give decision makers strong background information about a specific system in order to make reliable and economic planning of maintenance activities.

1.1 MAINTENANCE TECHNIQUES

Initial design and operations is not enough to ensure that a system is reliable and available for their whole operational life in order to perform predetermined tasks which are assigned by the user of those systems. The reason for this is, as operational time of physical assets increase, they tend to deterioration (Jardine et al., 2006). Thus to keep them functioning properly specific tasks like as cleaning, efficient repair and/or replacement of parts and components when there occurs a failure, safe storage when it is not used, lubricating, and so forth should be performed. These tasks and actions are part of Maintenance.

Maintenance indeed is the effective way to keep physical asset to perform under intended reliability and ensure that system availability is high. However, rapid repair of failed equipment is very critical issue to business succeed; because spending most of the time in maintenance tremendously decreases the capacity of the production system. Therefore it is crucial to determine optimum maintenance strategy. In addition Geert Waeyenbergh et al. argue that over a quarter of total workforces are responsible just for maintenance actions in some industries. Thus, by implementing effective maintenance strategy, cost for maintaining the system can be kept down.

With relevant to technological improvement the Maintenance concept also has been being developed. According to the framework proposed by Geert, before 1950, maintenance has not been recognized as an important action and items was fixed only when they fail. But between 1950 and 1975 need for maintenance emerged and industries assigned maintenance department for this job. At this period preventive maintenance was developed. And after 1975 the concept condition based maintenance began to attract researcher.

Generally maintenance policies can be categorized into three types. These are:

- *Improved maintenance (IM)*
- *Corrective maintenance (CM)*
- *Preventive maintenance (PM)*

1.1.1 Improved Maintenance

It is mentioned above that initial design and operations is not enough to avoid a physical asset to fail when it is operating. However, if the possible failure modes and conditions of operational environment of a product are considered at production stage then design can be made according to it, so that to eliminate or at least to lessen the need to maintenance actions. And this is exactly what it's done by improved maintenance policy.

1.1.2 Corrective Maintenance

In corrective maintenance actions are taken to retain a failed product or system to an operational state. Since, these actions are taken only when a system fails, they are either repairing it or replacing a failed component with new or used part.

Distinguishing characteristics of corrective maintenance is that since failure occurs suddenly, process of restoring a system to operational condition is unscheduled. That is why this maintenance is more costly than preventive maintenance for most cases. Thus critical components or failure modes, whose repair costs are expensive, should be avoided to fail frequently by applying other maintenance policies.

1.1.3 Preventive Maintenance

By the end of Second World War, as an effect of the war there was not sufficient workforce for the Industries. This situation led increase in mechanization. Jobs which were previously done by humans, now started to be done by machines. By 1950's there was more complex and numerous machines. As a result of huge dependency to mechanization, downtime become into sharper focus. In order to avoid downtime these machines had to be and could be prevented to fail. Thus the concept of Preventive maintenance came out (Moubray, 2001).

It is also clear from its name that, logic of preventive maintenance policy is about to prevent failure of critical equipments before they occur. It is designed to preserve and restore equipment reliability by replacing worn components before they actually fail. As an example to some preventive maintenance activities following actions can be mentioned, which are including partial or complete overhauls at specified periods, oil changes, lubrication and so on. In this maintenance technique, the role of workers also plays great role. They can record equipment deterioration and keep statistics so that to be able to know need for replacing or repairing of worn parts before they cause system to failure. The ideal preventive maintenance program would prevent all equipment failure before it occurs.

Depending on how it is performed, Preventive Maintenance can be classified as follows:

- Clock-based maintenance
- Age-based maintenance
- Condition-based maintenance

Because, there is common point connecting first two maintenances, which are Clock and Age based, they can be grouped under Periodic Maintenance. And throughout my thesis I will refer these preventive maintenances as Periodic maintenance after giving brief explanation.

1.1.3.1 Periodic Maintenance

Clock-based maintenance which is also called as Time-based maintenance is the traditional approach for Periodic maintenance. The mentality of this concept is that without depending on system's condition, it is performed according to calendar time. For example a company management can schedule that every/or some critical machines should be controlled in each week. In general, it is the maintenance of the system in time intervals.

On the contrary to Clock-based maintenance, the Age-based maintenance is performed not according to calendar time but according to system's operating time intervals or operating cycles (e.g., every 500 on/off cycles, or every 4000 h of flight).

Periodic Maintenance approach has an advantage and disadvantage as well. It is obvious that this maintenance concept is about to decrease downtime, caused by failure occurrences. In other words, every failure will lead downtime as its occasion, so by periodic maintenance this downtime will be decreased or even eliminated completely. However, increasing number of periodic maintenance action performed will cause downtime itself. It is because of that, in this technique whole system should be stopped in order to perform regular maintenance action, even if system is working properly.

In periodic maintenance policy the most challenging factor to be determined is maintenance period. Optimum maintenance period should be assigned in order to find minimum cost. However, it would be more accurate if we say optimum decision rather than minimum cost. The reason is that a company should find optimum point between intended reliability or/and availability level and their associated cost.

For example, if it is taken mean time to failure of same machine types in the past as maintenance period, then it would mean that half of the failures are expected before regular maintenance performed. In addition the higher the frequency is, the more time, money, and labor spent on maintenance; while the lower the frequency of maintenance is, the more the number of failures that occur before planned maintenance time. In order to maximize the system availability one can choose minimum time to failure as the maintenance period (Logenrand and Talkington, 1997), but as a result it will led to increase in unnecessary maintenance cost of healthy machines. Therefore, the maintenance period should be such that maximum availability of a system is assured under minimum cost of maintenance and minimum number of failure incidences. Figure1.1 illustrates this concept.

Choosing an appropriate maintenance task and scheduling period is combined with the criticality of the system or equipment. Criticality analysis is a measurement of the importance of the system from a functional point of view. Maintenance is done according to priority of criticality of system; criticality priority can be high or low. Periodic maintenance can be effective on non-critical machines, which have low priority of criticality; with less corrective maintenance. However, application of periodic maintenance on critical machines with high corrective maintenance cost may not produce an optimum solution. Deriving from this, a new approach of preventive maintenance model; condition-based maintenance is introduced.

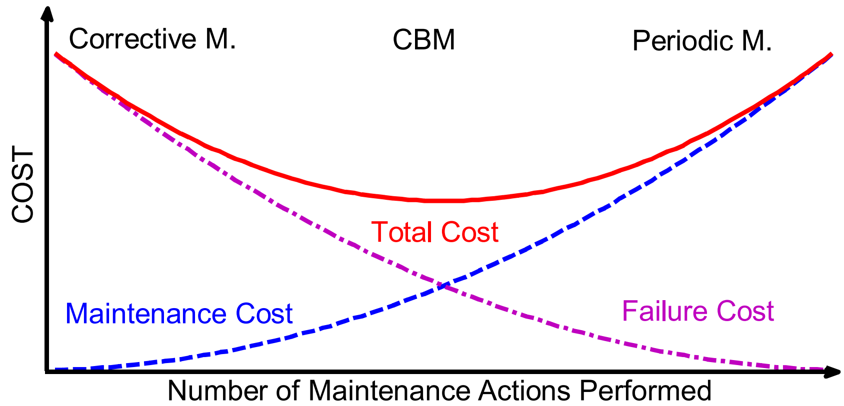


Figure 1.1 Illustration of the concept of optimal maintenance with failure and maintenance cost

1.1.3.2 Condition Based Maintenance

Condition Based Maintenance is the type of Preventive Maintenance which's aim is to detect impending failures and perform series of actions to prevent a system or physical assets from loosing their operational functions before they completely loose their functions as a result of breakdown. Working mentality of CBM is monitoring the condition of system health continuously, in order to minimize failure and maintenance cost, by analyzing real-time data acquired from different sensors which are set up to a system by an operator.

CBM is based on using real-time data to prioritize and optimize maintenance resources. Observing or monitoring the state of the system or machines is known as condition monitoring. This approach will monitor the whole system and determine the equipment's health, and react only when maintenance is actually necessary. By doing so, it keeps reliability and availability level within desired limits while eliminating unnecessary maintenance actions. CBM uses real-time data to reduce down time of system. Ideally condition-based maintenance will allow high availability of a system by minimizing spare parts cost, system downtime and time spent on maintenance. Besides, it will also allow maintenance personnel to know what and when to perform maintenance, which is also valuable information in order to decrease downtime cost.

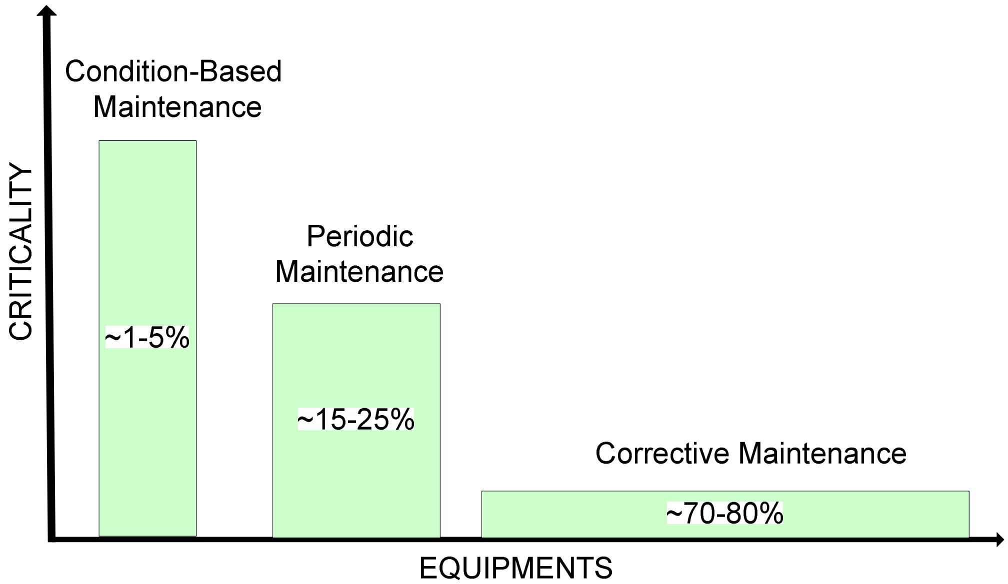


Figure 1.2 Maintenance techniques and their usage with equipment criticality

The most critical challenge of condition based maintenance is obviously its installation. Advanced electronics and improved instrumentations will be required for it. In most cases cost of installation is so expensive than the equipment itself. Often the cost of sufficient installation of equipment can be quite large, especially on equipment that is already installed. It is therefore important to decide whether your equipment is sufficiently important to justify the investment.

1.1.3.2.1 Benefits of CBM

Several factors that made condition based maintenance so popular are, being able to decrease failure cost in huge amounts, assuring security of a system and maximization of its availability (Logenrand et al., 1997). In addition CBM also allows improvement in system's reliability. Latter factor and reduction in failure cost can be especially highlighted among others. Subsections shown below illustrate benefits of CBM in more detail.

1.1.3.2.1.1 Cost Reduction

Cost reduction can be analyzed under four following categories (Allenby, 1990).

1. Machine Downtime Reduction

Machine breakdowns lead downtime of a system. CBM technique avoids this to happen by detecting a failure before it occurs. Therefore CBM enlarges production volume and increases machine utilization. It is estimated that $5 billion per year is would be saved US alone by application of CBM.

For example, in airway management, if there is detected a failure or/and some abnormal situation on aircraft then it will result in huge amount of cost. This cost will be, assigning another aircraft for the passengers who were going to have that flight, repairing the original plane, hotel bills and compensation (Friend, 2000). Therefore, detecting and preventing such abnormalities or the failures will remove these costs.

2. Maintenance cost reduction

By eliminating unnecessary regular periodic maintenance actions performed, CBM helps to reach maximum productivity of the system or equipment. It is estimated that effectively performed CBM technique may reduce cost by $9 billion per year (Douglas,1995). In addition Geert Waeyenbergh et al. argue that over a quarter of total workforces are responsible just for maintenance actions in some industries (Waeyenbergh et al., 2002).

3. Inventory Reduction

To store an item at warehouse will definitely have its corresponding cost. And, as the storage time increases the cost will also increase. Thus, it would be economic if the equipments are stored for less time period while also meet the requirements. In order to achieve this, one should know which component he will need, by what amount and when. In maintenance planning this can be achieved by CBM. Condition based maintenance allows to detect failures prior to their breakdown. As a result, it gives valuable information about which components have to be available in warehouse and when. Estimation was done that $6 billion could be saved by inventory reduction concept through effectively utilization of CBM.

4. Enhanced logistics and supply chain

Effective supply chain will decrease the overall cost. And in order to achieve it the health of the system should be known. CBM gives information about system therefore it enables to determine failures and effects of failures in advance. Once these are identified one is able to supply only necessary logistics from other companies. It is reported that when CBM performed effectively then amount of save achieved from only logistics and supply chain is estimated to be $15 billion annually in US.

As an example for the whole cost reduction, it is estimated that the amount which would CBM policy save in US alone, is $35 billion annually (Harbor Research,2003).

1.1.3.2.1.2 Availability and Safety

Increased mechanization in facilities led to huge dependency to machines, as a result downtime become into sharper focus. Avoiding downtime by keeping machines available to function and assuring that they are safe to be operated are major points in industrial manufacturing. These factors, especially safety should be considered at the same level or even higher with that of profit maximization and reduction in production cost. As an example we can say that military equipments, railway transportation, airway transportations have to provide high safety also should avoid delay which will cause punishment (Marquez et al., 2008).

1.1.3.2.2 General Process Diagram of CBM

Key steps in CBM program are consisting of:

- Data Acquisition
- Data Manipulation
- Condition Monitoring
- Diagnostics
- Prognostics
- Decision Support
- Presentation

These steps is shown in following figure

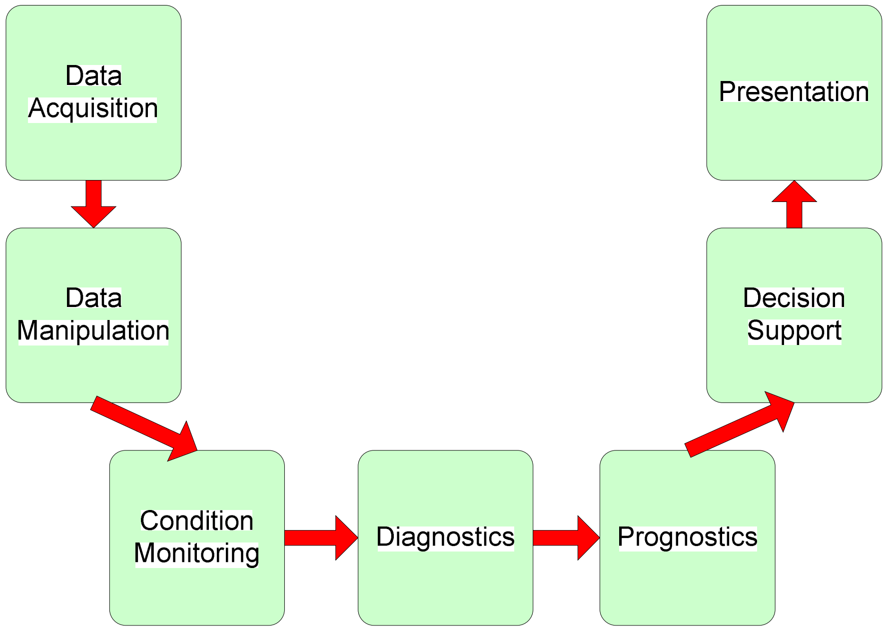


Figure 1.3 Process steps in Condition Based Monitoring

1.1.3.2.2.1 Data Acquisition (DAQ/DAS)

This is the process of collecting a data from physical assets or from a system. Data acquisition is the first step of CBM. These data can be studied under two categories, event data and condition monitoring data (Jardine et al., 2006). In first category information is continuously recorded on what happened and what was done. For example:

- January 1st , Installation of a system
- March 5th , System breakdown
- March 5th , New part installed
- April 1st Oil change and etc.

Second category includes measurements which are related to system health condition. These measurements are acquired by installing several sensors to a targeted physical asset. Installed sensors convert acquired data to electrical readable signals. At this point it would be better if we mention that CBM program does not have its fixed sensors, but types of sensors used can vary and depend on a system to which CBM is planned to be installed The most common data types that determine which sensors should be used are vibration signals and acoustic emissions. Several others can be listed as, ultrasonic signals, motor current, partial discharge, etc (Jardine et al., 2006). Consequently, acquired unprocessed data is sent to signal processing unit for further operations.

1.1.3.2.2.2 Data Manipulation (Feature extraction)

As it is mentioned above various types of sensors are installed onto a system or more precisely onto the machine or an equipment of a system in order to record the data related to the health condition of the machine/component. By these sensors, digital signals that encoded to velocity, pressure, force, acceleration, current, strain, and vibration of equipments are acquired. Data collected through sensors is classified as follows (Jardine et al., 2006)

- *Value type:* Data collected in specific time period are a single value. For example, temperature and pressure
- *Waveform type:* Data collected in specific time period are a time series, and it is often called waveform data. For example, current data and force data.
- *Multidimensional type:* Data collected in specific time period are multidimensional. Image data is the most common multidimensional data.

Data encoded from the sensor signals indeed contain information related to the health condition of the machine. However junk data and valuable data, that describe the equipment's health state, should be separated from each other. Data which have information related on system health is called features (Theodoridis and Koutroumbas, 2003), (Tou et al., 1974). And whole process is called feature extraction

The effectiveness of condition-based maintenance depends on quality of an extraction of machine features. In literature features are studied under following categories *time domain*, *frequency domain*, and *time- frequency domain* (or *mixed domain*) (Qian and Chen, 1996). Time domain features are the features that change in time such as crest factor, amplitude, kurtosis, and RMS values. Time synchronous average (TSA) is the popular time-domain feature analysis approach. Frequency domain features are the ones that have only frequency and amplitude information. Spectrum analysis by means of fast Fourier transform (FFT) is the most conventional one, which is used widely in frequency domain feature analysis (Jardine et al., 2006). The last one, that is joint frequency-time domain are the ones that have frequency and amplitude information in time.

1.1.3.2.2.3 Condition Monitoring

The process of system monitoring in order to determine sudden abnormalities or failures which cannot be detected in advance is called Condition Monitoring. These abrupt failures are possible to be detected by means of process monitoring techniques, which include statistical process control. Sudden failures are also called abrupt failures. Abrupt failures can be detected by process monitoring techniques, which include statistical process control (SPC) charts and other novelty detection methods. The logic of statistical process control is, by comparing data with control limits which are set by statistical methods, detecting sudden failures. Apart from statistical approach pattern recognition techniques are also employed in condition monitoring.

Condition monitoring can be defined as the process of finding abnormal behavior by learning the normal behavior of a system especially in case of insufficient failure data.

1.1.3.2.2.4 Diagnostics

Failure is defined also as, deviation of characteristic property beyond its control limit (Iserman, 1984). As it is clear from this, machines are not considered only when they completely loose their functionality. Thus, *Machine diagnosis* can be defined as the process of identifying, localizing and determining severity of a machine failure (Maynard et al., 1984). However for some failure types it is not possible to track their severity. For this reason failures can be categorized as abrupt failures and incipient failures. Abrupt failures are those mentioned above as untraceable of their severity. Because they happen in a very short time their development might not be tracked. The only way to detect them is, by departure of the features from the normal operating mode. On the other hand, incipient failures occur in time that is why their effects can be seen in the features in advance and their severities increase in time.

In case of incipient failure, even if machine work and behave normally in the early stages of the failure, its severity (i.e. health condition) can be detected. This will enable to prevent a failure to occur or to pass beyond its control limit.

1.1.3.2.2.5 Prognostics (Estimation of remaining usage life)

A Prognostic is a next step after diagnostics. And CBM prognosis is depended on how diagnosis quality is. Marquez calculated overall efficiency of CBM program as a multiplication of probabilities of diagnosis and prognosis. It is shown that perfect efficiency would be reached when probabilities of detection and prevention is 1 (Marquez et al., 2008). Briefly a prognostic is estimating the remaining useful life (RUL) of machines, physical assets, etc. by prediction of diagnosed failures. In literature various methods, algorithms have been developed on this area. Some can be listed as, artificial intelligence prediction, state-space tracking algorithms and higher-fidelity physics of failure algorithms.

There are to main prediction types which are, as mentioned above predicting remaining useful life of equipments, and the second one is predicting the chance that equipment will operate without any failure. However, in literature latter one is not so popular. There are only few papers in which it were studied, many researchers focused on RUL estimation (Jardine et al., 2006).

1.1.3.2.2.6 Decision Support

By analyzing the data from previous layers of CBM such as diagnostics, prognostic, and condition monitoring decision support recommends activities to be performed so that to optimize the maintenance decisions. Optimization of maintenance decisions mean reduced cost and at the same time increased system availability.

1.1.3.2.2.7 Presentation

The efficiency of this layer makes previous ones worthy. It creates the interaction between system and maintenance staff and also creates tools that guide the maintenance staff on complex maintenance procedures. By displaying virtual 2D-3D models, animations, and pointers on the Head Mounted Display (HMD) Augmented Reality Guided Maintenance System guides the maintenance operator through complicated maintenance activities. In this layer a chance of virtually experimenting of maintenance is given to maintenance personnel.

1.2 PROBLEM DEFINITION

As a part of my thesis I have worked at a project which is Development of failure prognostics and maintenance planning system for point mechanisms in Railways. We have applied my work as a case study. Thus, problem was economical analysis of maintenance strategies. It is about assigning maintenance strategies to failure modes so that overall cost would be optimum. We have three major units in our problem. And they are

- Maintenance Techniques
- Economic Analysis
- Railway Point Systems

Because, the first unit was mentioned earlier it will not be discussed again.

1.2.1 Economic Analysis

In order to make analysis of a system from economic point of view various types of economic tools can be implemented. In our model we will use Return on Investment and Life Cycle Cost methods.

1.2.1.1 Return on Investment/Rate of Return

ROI or Return on Investment which is also know as Rate of Return (ROR), is the measuring method in order to determine the value and/or efficiency of a specific investment in order to be able to compare that value with a bunch of other investments. Its simplicity made it popular among business environment. Evaluation criteria of ROI is that, if an investment shows a positive ROI then it means it will be profitable. Otherwise, if ROI is negative investment should be given up.

General method for calculation of ROI is shown below

$$ROI = (GainFromInvestment - CostOfInvestment) / (CostOfInvestment) \quad (1.1)$$

Generally return on investment is used to evaluate if a potential investment or business decision is worthy to be installed, or not.
Return on investment can be categorized into to groups which are single and multiple periods. Categories and subcategories

- Single-period
  - Arithmetic return
  - Logarithmic or continuously compounded return

- Multiperiod average returns
  - Arithmetic average rate of return
  - Geometric average rate of return
  - Internal rate of return

1.2.1.2 Life Cycle Cost Modeling

LCC is discounted projection of sum of investment cost, operating and maintenance cost to present day. It can be also described as identifying and quantifying of all costs which will be made from production stage and up to disposal of a physical asset (Woodward, 1997). According to LCC a firm can easily derive a conclusion about the certain project. For instance a firm may not wish to support an idea if it does not recover itself within certain year.

Life cycle cost is so important that it should not be overlooked in any business appraisal.

1.2.2 Railway Point Systems

Over the past decades, we can see a great population increase in the world, which had brought some problems along with. As an impact of growth in human number can be considered as depletion of some resources, including oil, food grains, water, and one of the most important issues from our side, which needs a serious attention, is transportation problem. In European countries, demand for extension of mobility is increasing greatly, including railway usage. One of the serious concerns to society is an accident that happened in recent years including Britain, Germany, Spain, and Turkey (Marquez et al., 2007). From its inception, railway industry has searched for ways to improve the performance of subsystems to achieve good levels of safety and reliability. Performance is highly related to increase of quality, safety, and reliability of services in railway infrastructure, that is why, nearly all researches that had been done up to day are concentrated on improving those critical issues

The 55% of railway infrastructure component failures on high speed lines are due to signaling equipment and turnouts (REMAIN, 1998). A term “signaling equipments” are bunch of special equipments, such as track circuits, interlocking systems, which includes signaling and plays great role over failure detection. Railway turnouts (also called points), consisting of switches and a crossing, area complex electro-mechanical devices which are exposed to severe environmental influences and which are essential for the operation of any railway bar horizontal lifts. From another point of view, annual cost of maintaining railway points is high. In order to achieve savings and ensure high availability and reliable and safe operation, points require regular inspection and maintenance also improved monitoring system. Primary performance measurement parameters of railway systems are speed of movement, vibration, supply voltage, power, temperature, throwing force, current and etc. Based on these parameters, failure detection can be done by the help of advanced electronics, sensors, transducers installed on railway turnouts.

Nearly all railway operations are done on railway turnouts (see Figure1.4) which is considered as complex mechanisms and assembled from switches and crossing where the moving parts are often described as 'points' (Marquez et al., 2003). Points allow a rail vehicle to move from one set of rails to another (see Figure 1.5 (Picture was taken from web site; http://seva.eng.ox.ac.uk)).

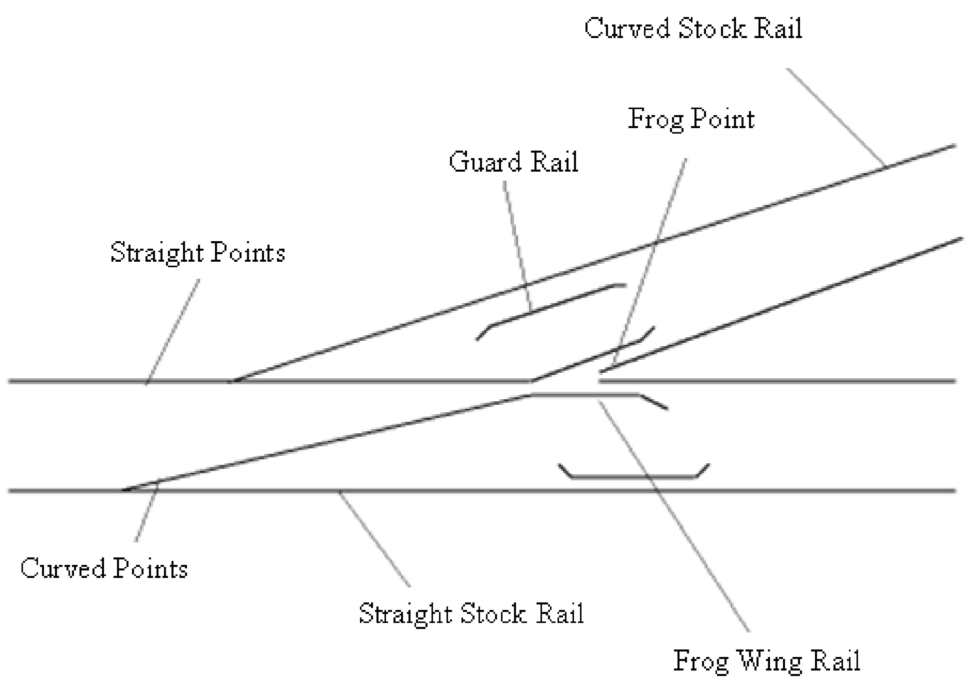


Figure 1.4 General diagram of Railway Turnouts

Standard point machine contain switch actuating mechanism and a locking system, which includes a hand-throw lever and selector level to allow railway operation be hand or power. There are many different actuation methods used in railway points such as hydraulically, manually and electrically. Point mechanism is normally divided into several major subsystems: the motor unit which include a contactor control arrangement and terminal area, a gearbox comprising spur-gears and a warm reduction unit with overload clutch and the dual control mechanism and the controller subsystem with motor cut-off and detection contracts (Marquez et al., 2003).

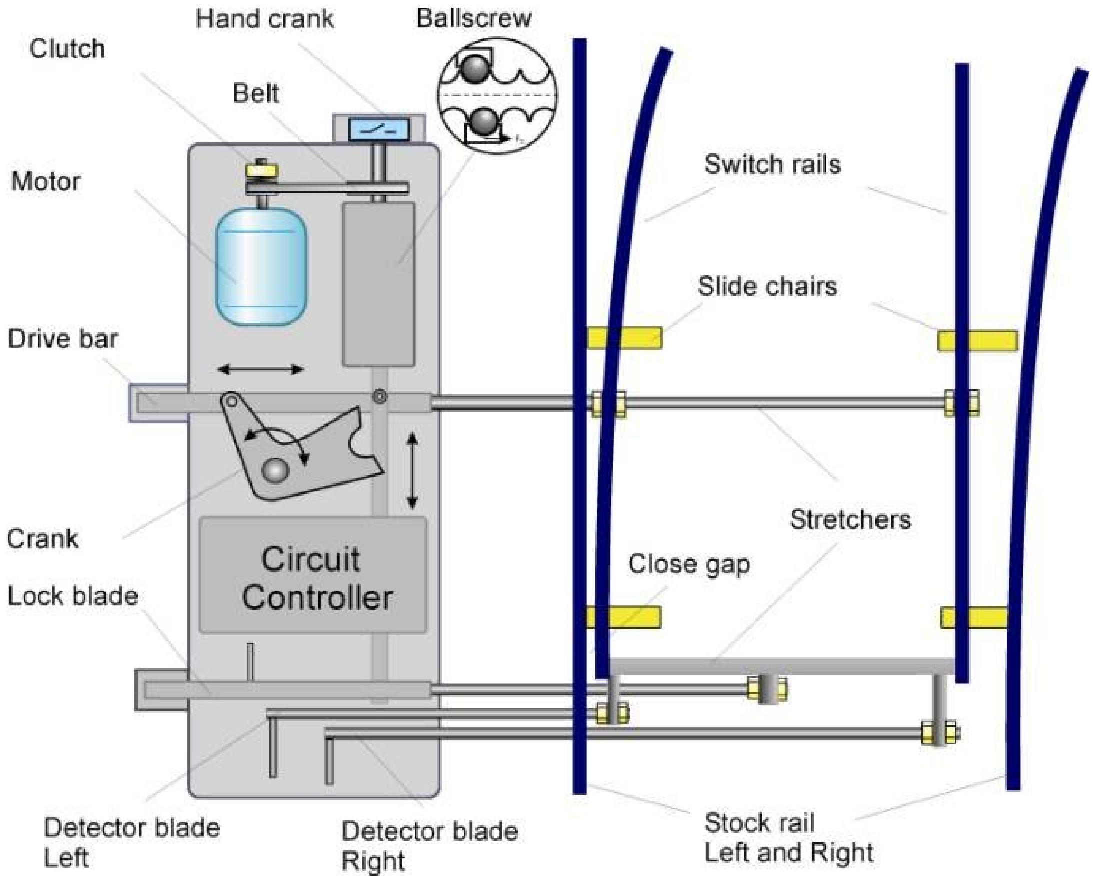


Figure 1.5 General Diagram of Point Mechanism (UTC, 2009)

The hand selector lever opens the motor supply circuit, disengages the drive from the motor and gearbox and engages the hand-throw lever drive. Arrangements of hand-throw lever and interlocking selector is possible to ensure that mechanism and points are returned to their original position before the power drive can be re-arranged.

The circuit controller includes detection switches and a pair of snap-action switches to stop the mechanism at the end of its stroke and to stop the motor electrically so that the mechanism is not subjected to impact loading. The detection switches have high-pressure wiping contacts made of silver/cadmium oxide or gold and they are operated by both the lockbox and the detection rod. In addition to that detection switches have additional contact to allow mid-stroke short circuiting of the detection relays to avoid wrong indications in the signal box or electronic interlocking controlling the points (Marquez et al., 2007).

The motor, which DC operation takes place, is a special heavy-duty design, developed specifically for point mechanism. It can take two basic forms, series-wound split-field and permanent magnet field on AC immune machines. Before the delivery of point mechanisms, all gear teeth, sliding surfaces and pivots are fully lubricated with molybdenum disulphide grease by the producer.

1.2.2.1 Single Throw Mechanical Equipment (STME)

Class of electro-mechanical equipment referred to as single throw mechanical equipment (STME), which is widely used equipment in many industrial applications for example automatic doors, mechanical presses, barrier systems, mass transit systems and in emergency train-stop mechanisms.

- An STME is used to move large non-linear loads from rest from one bounded position to another. This transition is known as a *throw*.
- It operates asynchronously upon the receipt of a control command, i.e. its operation is non periodical;
- Operation time which is known as throw time, is large compared with other reciprocating devices such as relays or switches;
- If operated in an open-loop configuration, speed-limiting mechanisms, such as dampers, are often used to ensure safe operation.

An STME has two stable states. Whenever activated, it physically moves from one state to another. Transition from state A to state B is a forward throw while that from state B to state A is a reverse throw.

1.2.2.2 Fault Conditions in Point Mechanism

As we stated above point mechanisms are an electro-mechanical devices which have potential faults. There are many types of faults that are seen in point machines which have potential affects to the operation of points. Maintenance of faults on point mechanism is done according to the seriousness of faults. We can subdivide faults as critical faults and non-critical faults. Critical faults require immediate attention, while non-critical faults may safely be dealt with during routine maintenance. The possibility of developing fault in the point mechanism depends on a large number of factors and fault conditions. Some of them are summarized below (Figure1.6) (Marquez et al., 2007):

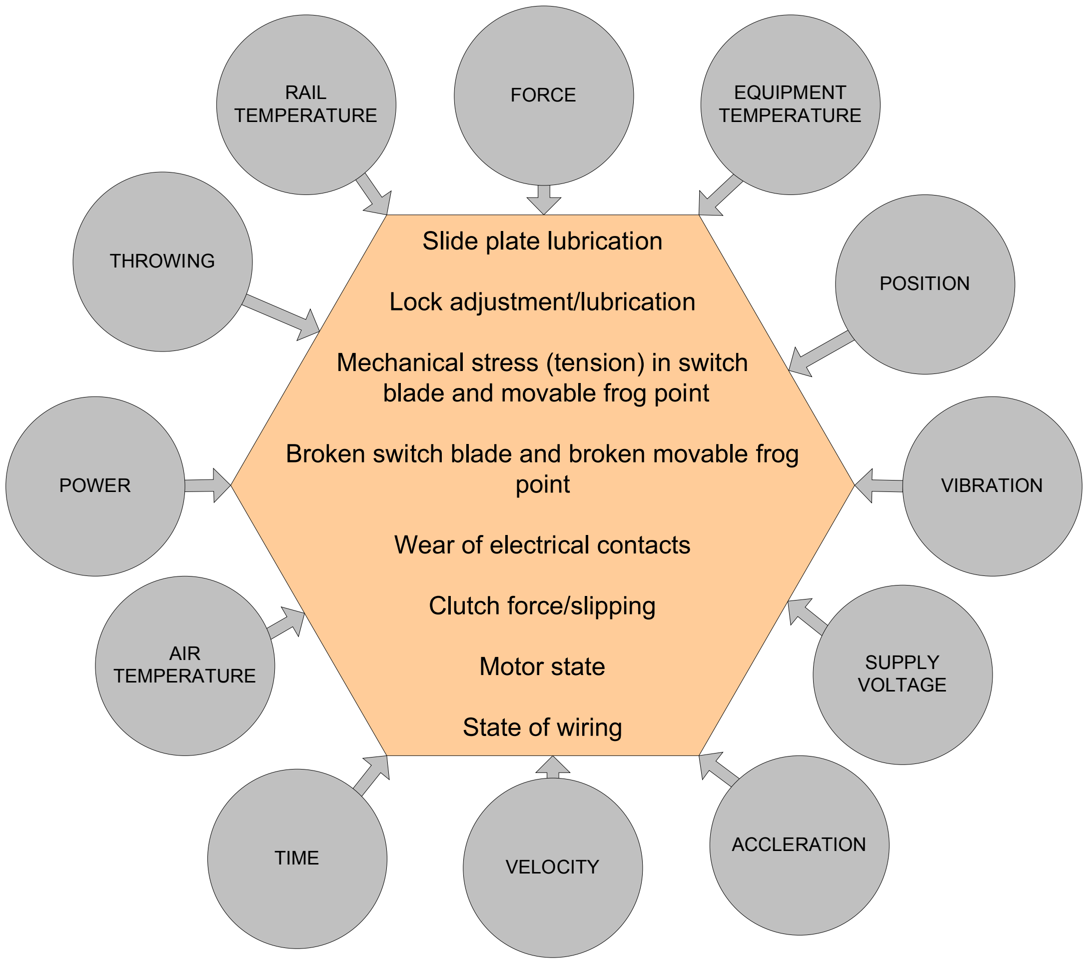


Figure 1.6 Factors influencing fault levels in point mechanisms

1.2.2.3 Potential Faults in Point Mechanism

Summarizations of some potential faults that are listed below which is seen in point mechanism with their Failure modes Table (See Table 1.1).

- Slide plate lubrication;
- Poor lock adjustment and/or lubrication;

- Mechanical stress (tension) in switch blade and movable frog point;
- Broken switch blade and broken movable frog point
- Wear of electrical contacts;
- Clutch force/slipping of clutch;
- Motor state;
- State of wiring;
- Obstruction at bearer on normal side of points;
- Obstruction at bearer on reverse side of points;
- Obstruction at toe on normal side of points;
- Back drive overdriving at heel on normal side with dry slide chairs;
- Back drive slack end off at toe end;
- Back drive slack end off at toe end (LHS side drive basket slack end off);
- Diode snubbing block disconnected;
- Dry slide chairs;
- Low tension on motor brush;
- Operational contact in original position;
- Tight lock on reverse side;
- Tight lock on reverse side (sand on all bearers on both sides).

Table 1.1 Failures modes and failures

	No	*Failure Modes*
Drive Rod	1	Drive Rod Out of Adjustment (OOA)
	2	Detector Rod Out of Adjustment
	3	Drive Rod Defective
	4	Detector Rod Defective
Slide Chair	5	Slide Chair Defective
	6	Slide Chair Obstructed/Contaminated
	7	Slide Chair Dry/Seized
Motor	8	Motor Brush Defective
	9	Commutator Defective
Detection Assembly	10	Contact Defective
	11	Detector Assembly HR
	12	Detection Assembly defective
	13	Detection Assembly OOA
Other	14	Micro switch Defective
	15	Relay Defective
	16	Stretch/Tie Bar Defective
	17	Face Point Lock
	18	Fuse Defective
	19	Stud Bolt Defective
	20	Cutout Reset Defective
	21	Heater Defective
	22	Cable Defective

CHAPTER 2

LITERATURE REVIEW

The previous work is discussed in two subsections: Maintenance strategies are discussed in the first subsection, whereas previous work on economic analysis of CBM system is discussed in the second one.

2.1 Maintenance Strategies

The concept of maintenance has changed over the years. Before 1950, maintenance has not been recognized as a profit factor and systems were fixed only when they breakdown (Waeyenbergh et al., 2002). In other words, Corrective Maintenance (CM) was widely implemented in industries. Between 1950 and 1975, need for Periodic Maintenance (PM) has emerged and companies assigned special departments for maintenance tasks. These departments perform maintenance in fixed periods. Periods can be either according to clock-based or age based. In the competitive environment of modern industry, high failure downtime/cost in CM and high maintenance downtime/cost in PM has led industry for more efficient solutions with less maintenance and failure downtime/cost. Even though the concept of Condition Based Maintenance (CBM) has started to be discussed after 1975 (Waeyenbergh et al., 2002), it is now possible to implement CBM with the technological advances occurred in recent years. In CBM, the system is observed real time with different sensors and the health of the system is identified and predicted using this sensory information (Camci F., 2005), (Roemer and Kacprzynski, 2000). CBM includes data acquisition, feature extraction and selection, condition monitoring, diagnostics, prognostics, and presentation layers. Readers are referred to (Dimla et al., 1997), (Jardine et al., 2006), (Djurdjanovic et al., 2003) for more information about CBM.

2.1.1 Condition Based Maintenance

An analysis is done over three distinct operating regions of motor current, to detect the noisiest part of current spectrogram. And after this process, filtration algorithms are applied to those datasets.
Upon the application of a moving average filter within a spectral analysis, authors stated that all kind of faults are detectable in both reverse-to-normal and normal-to-reverse directions of operation.

Over a few decades, an application of remote condition monitoring to railway point machines have played a major role in terms of reliability, safety and system availability of point machines. In (Marquez et al., 2007), they constructed a rule-based decision making algorithm in fault detection.

An approach which was carried out, in this present paper, was over operation current. Current curve was divided into 4-phases. And each phase has its own definition.

Phase-1: Variation in the current curve in this segment, the causes may relate to power supply, motor, friction clutch and gear box.

Phase-2: Variation in the current curve in this segment may be caused by faulty lock release device.

Phase-3: Variation in this phase is because of movable parts of the point, except electronic point machine.

Phase-4: Variation in this phase is caused by locking device problem.

Searching for non-faulty signals is very expensive business from the point of time and its cost. Due to this, authors of this present paper proposed digital filtering in order to increase reliability of the information presented to the rule-based decision making mechanism, using artificial perfect signals with random noise. In estimation of faults, Kalman filter (Kalman, 1960) was proposed. Using filtration and comparing them with fault-free signals, it was possible to detect higher proportion of faults. Aim was to develop condition monitoring system for predictive maintenance of point machines.

Railway point machine is electro-mechanical machines which have a lot of potential failures, which affects its normal operation in some points. In (Marquez et al., 2003), an algorithm was developed to detect gradual failures on point machines. Authors states that faults must be detected quickly and reliably if the information is useful. Reason of choosing dynamic system for their analysis was a model developed must be capable to identify faults in both operational directions (reverse-to-normal, normal-to-reverse).

Developed model in this present paper have 3 criteria, as follows:

1st Criteria- Based on whether the shape of the test data curve is irregular. If so, it is assumed to be consequence of a fault.

2nd Criteria- If the data in first criteria is not sufficient to detect faults, and then this criterion is applied. Find the maximum position of the curve and compare it with reference data. If the position of maxima is outside of band then it's considered as an indicative of fault.

3rd Criteria- If both 1st and 2nd is not sufficient in fault detection, then this present criterion is applied, whether the curve is symmetric with respect to maximum position, or not, with a margin of a given width. If this is the case, then it will be assumed to be a fault. This criterion is not used in real time.

They demonstrated the approach using data from tests on a commonly found point mechanism and included a discussion of the benefits of adopting a KALMAN Filter (Kalman, 1960) for pre-processing the data collected during tests. Kalman filter was employed to increase reliability of developed model presented to the rule-based decision mechanism.

Most problems with point mechanisms are associated with either wear of components or parts of railway point mechanism. Therefore, railway points require regular adjustment to compensate for wear in switch rails, cams and etc. Consequently, a dependable method of wear control is required. In (Marquez et al., 2007), proposed a method of robust remote monitoring system for assessing wear. It involves the collection and transmission of time varying data and the analysis of the signals. The authors put forward models to monitor wear, based on the signal analyzed for detecting the state of point mechanisms.

Proposed model in this paper belong to the so called Unobserved Components class of models implemented within State-Space framework. It searches for significant correlations between a reference curve and the new information coming from critical component, parameters are available. It's capable to detect wear and provide estimation for the behavior of worn set of points. The correlation between fault-free signals is considered as an indication of similarity between the curves. The model can detect all instances of wear in both operation directions.

In case of maintaining transit safety on railway systems, rails itself should be maintained properly from environmental hazards. In (Hernandez et al.) paper, authors made a research and stated results of microstructure and numerical simulation and corrosion analysis and effects of return (DC) current over rails. It is stated that rail base corrosion can shorten rail's life in many years or less and effects transit safety. Corrosion is caused by many factors including humidity, accumulated salts but mostly by return current (DC) from the transit car traction motors. And those factors accelerate the galvanic reactions that increase corrosion rate of the rail. The main objective of this research is to demonstrate by means of finite element analysis (FEA) the severity of rail base corrosion and to determine corrosion rates under different conditions. They stated that using plastic ties and return stray current system seem to be the most suitable solution to rail base corrosion.

In (Roberts et al., 2002), reasonable approach to fault diagnostics in a class of reciprocating, electro-mechanical equipment referred to as single throw mechanical equipment (STME) was developed. STMEs are widely used equipments in many industrial applications for example automatic doors, mechanical presses and barrier systems. As a case study electro-pneumatic machines were considered. Proposed approach distributes the fault diagnosis process using field bus data communication networks, which gives us minimum cost on fault detection. Authors proposed quantitative and qualitative methods based on abstract static models and structural residuals. Using decentralized fault isolation through a distributed architecture allows us full fault diagnosis of multiple assets to be carried out economically. The neuro-fuzzy system was trained in order to isolate faults between pre-defined failure modes. Hybrid approach was used for accurate fault diagnosis.

In 2000, the European Union founded a project named as "RAIL", which stands for; reliability centered maintenance approach for the infrastructure and logistics of railway operation, which concentrated on application of RCM technique to the railway mechanisms. And in this (Carretero et al., 2003) paper authors presented the results obtained from RAIL project, to perform RCM analysis, including cost aspects and maintenance planning guidance.

Present paper discusses the problems of installation of RCM to large scale railway infrastructure networks to achieve an efficient and effective maintenance concept. A methodology presented in this paper includes some new features to overcome the problems of RCM. This methodology has two types of benefits short and long-term benefits.

Short-term benefits:

- -Reduction of time and paper work.

Long-term benefits:

- -Increase of an equipment life and cost reduction.
- -Increase of production, decrease of downtime.
- -Reduction in parts and materials purchases.
- -Effective and up-to-date record of inventory reports.

As a result a developed methodology was installed to the signal equipments in several railway network sections.

As we mentioned before, a time series is a sequence of data points, measured typically at successive times, spaced at (often uniform) time intervals. A time series model generally reflects the fact that made observations close together in time species will be more closely similar than observations further apart and those close time data series will be put into same cluster by the help of some time series analysis algorithms.

Saranga and Knezeveic have studied methodology based on relevant condition predictor (RCP) for reliability prediction for systems under condition based maintenance (Saranga and Knezevic, 2001).

A mathematical model is developed for reliability prediction of condition-based maintained systems using RCP and Markov model. RCP- predicts critical values in the System and Markov model is used to model deterioration and fault recognition. In solving integral equations numerical approach is used.

In all system operations, maintenance cost is one of the most important concerns in system maintenance. Authors categorized maintenance strategies as corrective (reactive) maintenance and preventive (proactive) maintenance. The corrective maintenance attempts to restore a system after failure occurs. The preventive maintenance, on the other hand, is scheduled proactive maintenance which extends life of system and reduces number of failures and total maintenance cost. Preventive maintenance detects incipient failures and then replaces or repairs equipment according its condition (Lu S. et al., 2007).

As stated in this present paper, condition based maintenance (CBM), is used to increase effectiveness of preventive maintenance. CBM is a strategy to make maintenance decision according to the actual state or actual deterioration of a system that is monitored over a time. It's widely recognized as cost-effective maintenance. There are many different methods developed over CBM. In system degradations some CBM approaches were developed such as Markov chain with multiple discrete states (Albin and Chao, 1993 and Liao et al., 2006). In modeling a continuous degradation state of system, some researchers proposed cost minimization methods, considering cost of replacement, failure and maintenance (Dieulle et al., 2003; Grall et al., 2002). In most CBM approaches, a monitored deterioration measures are compared with predefined threshold for preventive maintenance. If an actual deterioration measure exceeds threshold then the system will be called for preventive maintenance. In other words, instead of using current deterioration measures for decision-making, the predictive CBM (PCBM) predicts the condition of system deterioration in the future for decision making. And prediction is done by adaptation of state-space model and Kalman filtration. Another advantage of PCBM, which is presented in this paper, is; system degradation states are modeled as continuous by state-space model which includes degradation level and degradation rates and those criteria play a major role on influencing a maintenance decision.

Finally maintenance decision making takes place, according to predicted failure probabilities, associated with preventive and corrective maintenance cost, and profit loss because of system performance deterioration.

Demand for high quality rail services are increasing year by year. All maintenance regimes of railway system must be tightened in order to meet expectations. If cost were not an issue, railway systems could be improved be up-to-date techniques in order to increase the transit safety. Hence several methods have been developed under condition based maintenance. New condition monitoring approach is introduced, in which they describe two important aspects, one on the rail and one on the train. In their experiment, developed condition monitoring system monitors the strains of both system using optical sensors. The reason of using optical sensors instead of conventional strain gauges is that optical sensors are immune to electromagnetic fields (Ho et al., 2006).

As a result, authors of this present paper have developed very powerful condition monitoring system using Fibre Bragg Grating (FBG) sensors to monitor the rail tracks and train borne equipment and were tested on frequently used mainline railway.

Authors of case study developed a forecasting system for vibration analysis based on bivariate vibration signals which was acquired from equipment by portable data acquisition system in order to improve the diagnosis in a condition monitoring of critical equipment. The system developed in this case study allows one to detect failures in machines of recent acquisition. It also allows having a diagnosis system that helps the analyst, either by indicating the presence of an anomaly or by confirming diagnoses produced by the condition monitoring program of equipment(Pedregal and Carnero, 2006).

2.2 Economic Analysis

In condition based maintenance, common way is to monitor the system and record the data which is acquired via some sensors and if those acquired sensory dataset exceeds a pre-set critical level, equipment monitored is declared as faulty and replacement or repair may be applied. However, very little attention has been paid to whether or not predefining critical level and monitoring interval is done or set in cost effective way. This paper (Wang, 2000) introduces a new developed model that can be used to determine the optimal critical level and monitoring interval in condition based maintenance. As it is stated, determination of critical level and monitoring interval has very important influences on CBM. If critical level is set to very low level, your system remains healthy which means number of failures of equipment may be decreased but in contrary to this the number of preventive maintenance will increase which is very costly business. On the other hand, if critical level is set to high level, the number of preventive maintenance will be decreased but may result in increased risk of failure. Both case one and case two effects operational efficiency and production cost of manufacturing industries. The same argument also seriously concerns monitoring interval of system.

In this present paper, developed model studies the relationship between critical level and monitoring interval in terms of cost, downtime and other criterion interests. Authors developed their model on the bases of random coefficient growth model (Lu and Meeker, 1993), which means regression growth model coefficients are explored by density distribution probabilities. Random coefficient growth model was used to state deterioration of monitored equipment, once its performed they established decision making model which was the first aim of this work. This random coefficient growth model was used in pharmacokinetics, economics and social sciences by many researchers such as Lindstrom and Bates (1990), Mallet (1986), Feldman (1988), Sheiner and Beal (1980,1981,1983) and Johnson (1977, 1980). Many researchers applied in this random coefficient growth model in their work but a few of them used in CBM and most important thing that makes this work unique from others is none of them determined optimal critical level of system in their work.

Finally, developed model which finds optimum solution, in this present paper, for those above mentioned problems was supported with a simple example to show the effectiveness of modeling idea.

FMECA (Failure Model Effect and Criticality Analysis), which was developed by NASA in 1960s and used in Apollo project, is a process of determining criticality and effects of failure modes (Carmignani, 2009). This analysis ranks failure modes from most critical to less, by evaluating three factors: Severity, Occurrence and Detection. FM having greatest Risk Priority Number (RPN) is the most critic failure and it is a product of; Severity (S), Occurrence (O) and Detection Probability (D) (Carmignani, 2009)

$$\mathbf{RPN}=\boldsymbol{S}\times\boldsymbol{O}\times\boldsymbol{D} \quad (2.1)$$

Analysis of failure modes without their economic consequences will not be complete. Carmignani has developed a FMECA model that takes economic aspect of failure modes into consideration (Carmignani, 2009). He introduces a model that enables finding the best mix of failure modes to be maintained according to budget constraints.

Marquez made an economic analysis of condition based maintenance for railway turnout systems (Marquez et al., 2008). Life cycle cost (LCC) of railway turnouts when condition monitoring is applied is calculated. The turnout system is considered as a whole and applying CBM for all components and failure modes is studied in this work. However, the importance and/or criticality of components/failure modes may be different in a system, in which some failure modes may require CBM, some PM, and even some can go with CM. In other words, the investment of CBM may not be necessary for some of the failure modes.

As mentioned above, the main aim of monitoring the system is to record and obtain useful information that can be used in diagnosis and analysis of system maintenance. Inspection itself does not reduce occurrence of failures and the number of repair or replacement. But only integrating the system with condition monitoring does reduce repair number and impending failure modes. In this paper (Coolen and Dekker, 1995), authors analyzed a basic model for optimization of inspection technique economically. The model assumes that inspection detects one type of failure mode when the system passes trough intermediate state. But there might be other failure modes for which inspection technique (condition measurement) can not detect an intermediate state (phase-2) which is called competing risk. In this work, influence of competing risk on inspection technique was analyzed and cost-effectiveness of the condition monitoring had been established. Once establishing cost-effectiveness of condition monitoring there is no need to determine optimum condition monitoring intervals. The 2-phase model, which was used to determine critical inspection time to minimize a cost-rate, is semi-Markov model representing life and deterioration of a system.

Confirming anomalies in a smaller time interval increase the safety of the industrial plants. Whole system which was developed in this work relies on statistical model in a state space framework with an well-known filtration algorithm Kalman filter and associated recursive algorithm known as fixed interval smoother.
This developed model was combined with a cost model in conditioned monitoring proposed by Christer (Christer et al., 1997) and generalized to the multivariate signal case by Pedregal and Carnero (Pedregal and Carnero, 2006), by which the time of preventive maintenance is produced when the minimum expected cost per unit of time is reached in the future.

Such a measure is a combination of the costs of failure, the costs of a preventive replacement and the probabilities of reaching the alarm levels fixed by some criteria.
The statistical system is set up such that the local mean level of the vibration state of the equipment is estimated directly from the data, based on a continuous-time set-up. The main reason for using the continuous-time model in estimation of vibration state of the equipment is that the data available come from the physical system at irregular sampling intervals.

CHAPTER 3

ECONOMIC ANALYSIS MODEL

3.1 MATHEMATICAL BACKGROUND

- **Weibull distribution**

Weibull distribution is a continuous probability distribution. It was first identified by Fréchet (1927) and first application made by Rosin & Rammler (1933). However Waloddi Weibull described it in detail in 1951, thus it was named after him.

General formula for Weibull probability density function is as follows:

$$f(x) = \frac{k}{\lambda}\left(\frac{x-\theta}{\lambda}\right)^{k-1} e^{-\left(\frac{x-\theta}{\lambda}\right)^{k}} \tag{3.1}$$

where,

$$f(x) \geq 0,\ x \geq 0 \text{ or } \theta,\ k \succ 0,\ \lambda \succ 0,\ -\infty \prec \theta \prec \infty, \tag{3.2}$$

and,

λ: Scale parameter,

k: Shape parameter,

θ: Location parameter

This is three-parameter weibull distribution. However, by setting θ=0 we will get two-parameter weibull distribution. And formula will be as follows:

$$f(x) = \frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{k-1} e^{-\left(\frac{x}{\lambda}\right)^{k}} \tag{3.3}$$

In one-parameter weibull distribution θ=0 and shape parameter stays constant as shown below:

$$f(x) = \frac{C}{\lambda}\left(\frac{x}{\lambda}\right)^{C-1} e^{-\left(\frac{x}{\lambda}\right)^{C}} \qquad (3.4)$$

In our model we assume that shape parameter is always greater than 1. Because there are three failure types which are;

- Infant Mortality (k<1): These types of failures occur at beginning stages of usage. And the reason usually is, manufacturing problems. Thus, these failures can be prevented to occur at production stage

- Sudden Failure (k=1): These failures occur completely randomly. Randomness makes it difficult to track its development

- Incipient Failure (k>1): Occurs slowly which enables to track its development and improve health state estimation techniques.

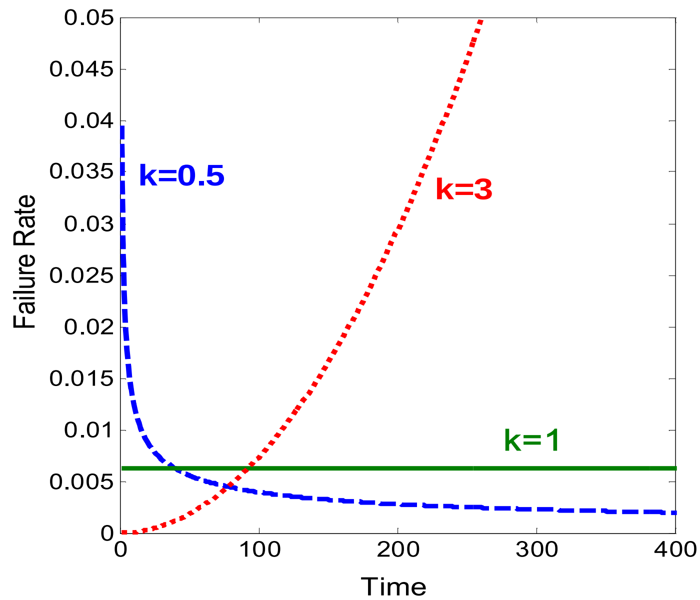


Figure 3.1 Effect of shape parameter on Weibull failure rate function

- **Return on Investment/Rate of Return**

ROI or Return on Investment which is also know as Rate of Return (ROR), is the measuring method in order to determine the value and/or efficiency of a specific investment in order to be able to compare that value with a bunch of other investments. Its simplicity made it popular among business environment. Evaluation criteria of ROI is that, if an investment shows a positive ROI then it means it will be profitable. Otherwise, if ROI is negative investment should be given up.

General method for calculation of ROI is shown below

$$ROI = (GainFromInvestment - CostOfInvestment) / (CostOfInvestment) \quad (3.5)$$

Generally return on investment is used to evaluate if a potential investment or business decision is worthy to be installed, or not.
Return on investment can be categorized into to groups which are single and multiple periods. Categories and subcategories

- Single-period
  - Arithmetic return
  - Logarithmic or continuously compounded return

- Multiperiod average returns
  - Arithmetic average rate of return
  - Geometric average rate of return
  - Internal rate of return

3.2 MODEL

The model aims to minimize the total cost of maintenance and repair for a system, which includes several possible failure modes, by assigning each failure mode to one of three maintenance policies (i.e., CM, PM, and CBM). Figure 3.2 illustrates the input-output scheme of the presented model. The input parameters are given in Table 3.1

Table 3.1 Input parameters

Reliability Information	
Accuracy (detection rate) of CBM model for failure mode *j*	ψ_j
Weibull shape and scale parameters of failure mode j	A_j, B_j
Failure Mode & Maintenance Information	
Failure Mode Corrective Maintenance Action Tree Matrix	$CA_{j,k}$
Failure Mode Periodic Maintenance Action Tree Matrix	$PA_{j,k}$
Failure Mode CBM Action Tree Matrix	$BA_{j,k}$
Number of periodic maintenance incidents to be performed in a given time period	Nm
False alarm rate for failure mode *j*	FAR_j
Expected down time for Corrective Maintenance when FM j occurs	$E(D_j)$
Expected downtime for maintenance of failure mode j	$E(PD_j)$
Expected downtime for maintenance of failure mode j	$E(CmD_j)$
Repair Action Time of action k for failure mode j	$RAT_{j,k}$
Expected downtime for false alarm of failure mode *j*	$E(CfD_j)$
Economic Parameters	
Down time cost per one time unit (e.g., minute)	Cd
Cost of Corrective Maintenance action step *k* for failure mode j	$CCA_{j,k}$
Cost of Periodic Maintenance action step *k* for failure mode j	$CPA_{j,k}$
Cost of CBM action step *k* for failure mode j	$CBA_{j,k}$
Fixed operating and support cost of CBM	FOC
Fixed investment cost of CBM	$FInvC$
Investment cost of CBM for failure mode *j*	IC_j
Operating cost of failure mode *j* in CBM	OC_j

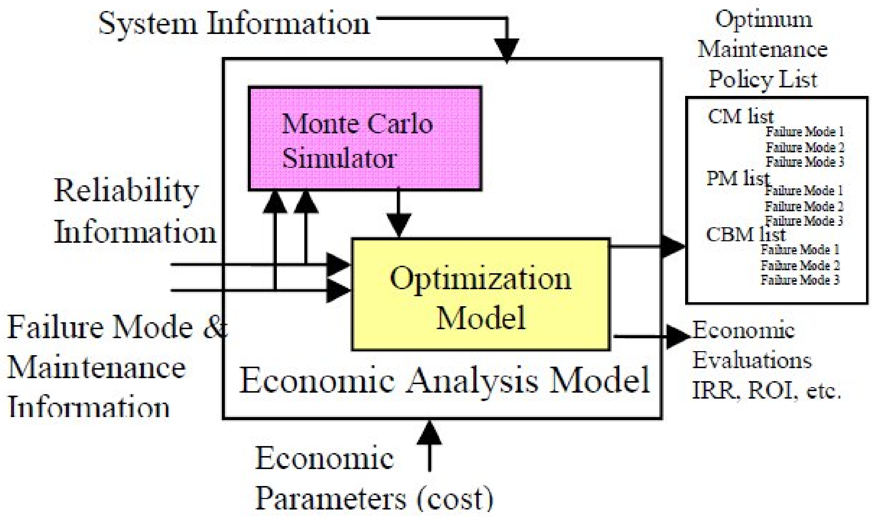


Figure 3.2 Input Output scheme of economic analysis model

The presented model aims to minimize the total maintenance and failure cost. Cost can be considered as money or down time or both. The objective function to be optimized involves three main terms, each representing the cost of a maintenance policy (CM, PM, CBM) for a given failure mode. Costs of CM, PM, CBM are represented with $i = 1, 2 \text{ and } 3$, respectively as in Eq. (3.6). The constraint given below ensures that each failure mode will be considered under only one (exactly one) maintenance policy.

$$\sum_{i=1}^{3}\left(FC_i \times \min\left(1, \sum_{j=1}^{N} X_{i,j}\right) + \sum_{j=1}^{N} X_{i,j} \cdot C_{i,j} \right) \qquad (3.6)$$

s.t. $\forall i : \sum_{i=1}^{3} X_{i,j} = 1$

$X_{i,j}$: 1 if failure mode j to be maintained based on maintenance policy i (CM if $i = 1$, PM if $i = 2$, CBM if $i = 3$), 0 otherwise.

$C_{i,j}$: Cost of maintaining failure mode j in maintenance policy i

FC_i : Fixed Cost (e.g., investment, operation & support cost) of maintenance policy i

$FC_1 = 0$, $FC_2 = 0$, No fixed cost in CM & PM

The first term in calculation of a given maintenance policy (in eq. (3.6)) represents the fixed cost to be incurred when it is initially applied, which basically represents the initial investment, fixed installation and operating & support cost. This cost is identified as 0 for corrective and periodic maintenance since there is no investment cost and these policies are currently being applied in industry. On the other hand, a company needs to spend an initial cost to be able to apply CBM in a system. This cost will be spent once when at least one failure mode is decided to be maintained with CBM. The second term in Eq. (3.6) represents the maintenance and failure cost of given failure mode / component with the corresponding maintenance policy. Cost of each maintenance policy ($C_{i,j}$) is discussed in detail in following subsections.

3.2.1 CORRECTIVE MAINTENANCE

Corrective maintenance includes only the repair cost, since no maintenance is performed before failure. Repair is more costly than maintenance and in general CM is applied in non-critical components or failure modes, whose repair costs are cheap. Cost of CM is basically product of expected number of failures given no maintenance is planned and cost of each failure incident as shown in eq. (3.7).

$$C_{1,j} = E(FM_j \mid M = 0) \times \left(E(D_j) \cdot Cd + E(CD_j) \right) \qquad (3.7)$$

$FC_1 = 0$, No fixed cost in CM

$C_{1,j} =$ Corrective maintenance cost of failure mode j

$E(FM_j \mid M = 0)$: Expected number of j^{th} failure mode incidents given 0 maintenance performed

$E(D_j)$: Expected down time when FM $_j$ occurs

Cd : Down time cost per one time unit (e.g., minute)

$E(CD_j)$: Expected repair cost of FM $_j$

Cost of each failure incident consists of downtime cost and actual repair cost as shown in eq. (3.7). Downtime cost is the loss that occurs as a result of system being down such as production loss, or cost of unavailability, etc. and calculated as the product of expected downtime for failure mode j ($E(D_j)$) and cost per time unit downtime (Cd).

Even if sufficient information about number of failures in a given period exists, reliability information obtained from similar equipments may be used for calculation of expected number of failures for different cases with different maintenance periods. Reliability information gives the progression of component failure probability in time as represented in Figure 3.3.The failure probability increases as the time passes after maintenance, repair or component replacement

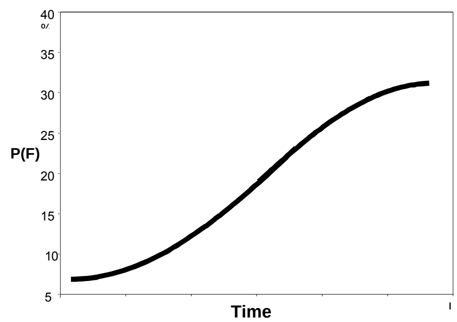
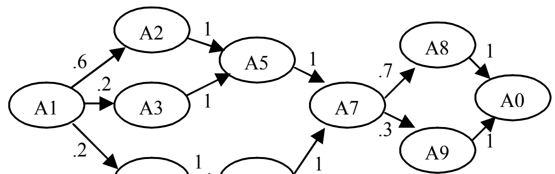


Figure 3.3 Reliability (Failure Probability) of a component

Repair down time depends on the actions to be performed during the repair. External factors such as waiting for some unavailable part can also be added as an action. In a repair process, the actions to be performed can be modeled as a decision tree. Each level in decision tree (to be called as action tree) represents a step in repair and there exist several possible actions to be performed in each level. Each action is associated with a probability value. Figure 3.4 represents an action tree and displays action probabilities. Expected downtime is the sum of product of action probability and action duration (time takes to perform action) for all failure modes as illustrated in equation (3.8).



A1	A2	A3	A4	A5	A6	A7	A8	A9	A0
1	.6	.2	.2	.8	.2	1	.7	.3	1

Figure 3.4 Action Tree for repair

$$E(D_j) = \sum_{k=1}^{y} P(CA_{j,k}) \times RAT_{j,k} \qquad (3.8)$$

$P(CA_{j,k})$: Probability of action *k* for failure mode *j* for CM policy

$RAT_{j,k}$: Repair Action Time of action *k* for failure mode *j*

y : Number of all possible actions to be performed

When the action probabilities are multiplied by the cost of action instead of time, expected repair cost ($E(CD_j)$) will be obtained as in Eq. (3.9). It may also be obtained from historical data, if available.

$$E(CD_j) = \sum_{k=1}^{y} P(CA_{j,k}) \times CCA_{j,k} \qquad (3.9)$$

$CCA_{j,k}$: Cost of action step *k* for failure mode *j* for CM

Expected downtime can be obtained from historical data or calculated incase of unavailable data. If sufficient number of the given failure mode has occurred before, the average waiting time is the expected down time. Otherwise, time of every possible repair action in decision tree will be considered to calculate the expected downtime.

3.2.2 PERIODIC MAINTENANCE

Periodic maintenance cost includes two terms: repair and maintenance cost.

$$C_{2,j} = MaC_j + FaC_j \qquad (3.10)$$

$FC_2 = 0$, No fixed cost in PM

$C_{2,j}$: Periodic maintenance cost for failure mode *j*

MaC_j : Maintenance cost for failure mode *j*

FaC_j : Failure Cost for failure mode *j*

Maintenance cost is the product of number of maintenance incidents and cost of each maintenance. Cost of each maintenance is the sum of maintenance downtime and actual maintenance cost as in eq. (3.11).

$$MaC_j = Nm_j \times \left(E(PD_j) \cdot Cd + \sum_{k=1}^{y} \left(P(PA_{j,k}) \cdot CPA_{j,k} \right) \right) \qquad (3.11)$$

$P(PA_{j,k})$ = Probability of action k for failure mode j for PM policy

$CPA_{j,k}$: Cost of maintenance action step k for PM

Nm_j : Number of maintenance incidents to be performed in a given time period for failure mode j

$E(PD_j)$: Expected downtime for maintenance of failure mode j

Failure cost is the product of a failure incident cost and expected number of failures. Since the system is maintained periodically, expected number of failures highly depends on the maintenance period. Similar to calculation of expected number of failures in CM, Monte Carlo simulation will be used to calculate the expected number of failures given the maintenance period. In contrary to calculation of expected number of failures in CM, part of the reliability data will be used in calculation of expected number of failures in PM. Reliability data will be cut in the maintenance point since the failure probability will be reduced with maintenance as illustrated in Figure 3.5. Expected number of failures till maintenance is calculated using Monte Carlo simulation with part of the reliability data from beginning to the maintenance point. This number will be multiplied by the number of periods (i.e., number of maintenance +1) in order to calculate the number of failures in the given time frame. This again will be repeated in large numbers in order to approximate the expected number of failures with given number of maintenance.

$$FaC_j = E\left(FM_j \mid M = Nm \right) \times \left(E(D_j) \cdot Cd + E(CD_j) \right) \qquad (3.12)$$

$E(FM_j \mid M = Nm)$: Expected number of failure incidents of failure mode j given Nm number of maintenance performed in given period

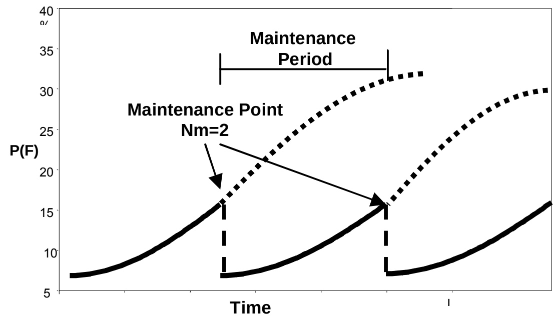


Figure 3.5 Reliability (Failure Probability) of a component

3.2.3 CONDITION BASED MAINTENANCE

Different from PM and CM, Condition Based Maintenance (CBM) requires investment, and operating costs. Investment cost is the cost of development, testing, installation of CBM technologies, training personnel, etc. for the system. Operating cost is the cost of making CBM up and running including replacement of sensors or other equipment when necessary.

Operating and investment costs consist of two terms: fixed cost and failure mode cost as in Eq. (3.13) and (3.14). First term is the fixed cost, which is the cost to be incurred when at least one failure mode is planned in CBM policy. Second term involves the investment and operating cost of CBM for each failure mode.

$$InvC = FInvC + \sum_{j=1}^{N} \left(X_{3,j} \times IC_j \right) \qquad (3.13)$$

$InvC$: Investment Cost

$FInvC$: Fixed Investment Cost

IC_j : Investment cost for failure mode j

$X_{3,j}$ =1 if failure mode j is maintained under CBM

$$OC = FOC + \sum_{j=1}^{N} \left(X_{3,j} \times OC_j \right) \qquad (3.14)$$

OC : Operating Cost

FOC : Fixed Operating Cost

OC_j : Operating cost for failure mode *j*

Due to the nature of the optimization formulation, the fixed costs of operating and investment cost are written together under the fixed cost of CBM as in eq. (3.15). Operating and investment costs of failure modes are written with failure and maintenance costs as in eq. (3.16).

$$FC_3 = FInvC + FOC \qquad (3.15)$$

$$C_{3,j} = OC_j + IC_j + FaC_j + MaC_j \qquad (3.16)$$

$C_{3,j}$: CBM cost for failure mode *j*

Even though CBM aims to detect the failures before it happens, there will be cases, in which failures could not be detected on time with CBM system (called missed failures). Failure cost in CBM is the product of expected number of missed failures and repair cost. In most diagnostics methods, the detection rate is evaluated and reported. Expected number of missed failure incidents is the product of miss ratio and expected number of failure incidents as in eq. (3.18).

$$FaC_j = E(N_{ss_j}) \times \left(E(D_j) \times Cd + E\left(CD_j\right) \right) \qquad (3.17)$$

$E(N_{ss_j})$: Expected number of failure incidents that will be missed by CBM for failure mode *j*

$$E(N_{ss_j}) = (1 - \psi_j) \times E(FM_j \mid Nm = 0) \qquad (3.18)$$

ψ_j : Accuracy (detection rate) of CBM model for failure mode *j*

In CBM, maintenance is performed when an alarm is given. An alarm given by CBM may be true (failure detected) or false (false alarm, no real failure). Thus, maintenance cost is the sum of the cost of detected and maintained failures and cost of false alarms as in eq. (3.19).

$$MaC_j = TrM_j + FaM_j \qquad (3.19)$$

TrM_j : Maintenance cost of early detected failures for failure mode *j*

FaM_j : Maintenance cost of false alarms for failure mode *j*

The cost of maintenance for detected failures is the product of number of true alarms given by CBM and cost of each maintenance action, which is the sum of downtime and maintenance cost, as shown in eq. (3.20). Maintenance cost when the failure is detected is usually less than standard periodic maintenance cost since some knowledge is gained about the problem with CBM such as symptoms, possible failure mode, etc. before starting the maintenance. In addition, expected downtime is also less than downtime of periodic maintenance due to the same reason.

$$TrM_j = E\left(N_{a_j}\right)\left(E(CmD_j)\cdot Cd + \sum_{k=1}^{y}\left(P(BA_{j,k})\times CBA_{j,k}\right)\right) \qquad (3.20)$$

$E(N_{a_j})$: Expected number of correctly detected failure incidents for FM *j*

$E(CmD_j)$: Downtime for maintenance of failure mode j when a true failure is detected

$P(BA_{j,k})$: Probability of action *k* for failure mode *j* for CBM policy

$CBA_{j,k}$: Cost of maintenance action step *k* for CBM

Expected number of true detection is the product of accuracy of CBM model and expected number of failures given no periodic maintenance is performed and displayed in eq. (3.21).

$$E(N_{a_j}) = \psi_j \times E(FM_j \mid Nm = 0) \qquad (3.21)$$

In case of false alarm no maintenance is performed, since there is no really failure. However, understanding that the alarm was false requires some inspection. Thus, cost of false alarm is the sum of downtime and inspection cost. Down time of false alarm might be high, since ensuring that the alarm was really false may take time. Inspection cost may be low, since it does not involve any repair or maintenance.

$$FaM_j = E\left(FN_j\right)\left(E(CfD_j)\cdot Cd + \sum_{k=1}^{y}\left(P(IA_{j,k})\times CIA_{j,k}\right)\right) \qquad (3.22)$$

$E(CfD_j)$: Expected downtime for false alarm of failure mode *j*

$E(FN_j)$: Expected number of false alarms for failure mode *j*

$P(IA_{j,k})$: Probability of action *k* for failure mode *j* for inspection in CBM

$CIA_{j,k}$: Cost of inspection step *k* for failure mode *j* in CBM

CHAPTER 4

IMPLEMENTATIONS AND RESULTS

The presented method is applied to two case studies on railway turnout systems. The first case study is from a turnout system in United Kingdom and data such as failure types, their frequencies, and down times are reported in (Marquez et al., 2008). The second case study involves the failure data from turn out systems in one region of Turkish State Railways.

The importance of railway system that includes trains, metro, and tramway has been increasing in the world. According to the report of European Commission, it is expected that the passenger and cargo transportation in railways in Europe will be doubled and tripled, respectively in 2020 (Marquez et al., 2008). It is obvious that this demand increase cannot be satisfied with only building new railways, the efficiency of existing and new railways should be increased. This could be achieved by increasing the availability of railways with minimum cost, which is directly related with repair, maintenance frequency and cost. For example in England, 3.4 million pound is spent every year for maintenance of point machines in 1000km of railways (Marquez et al., 2008). In addition, maintenance and repair of point machines are related with not only cost due to passenger delays, but also passenger security. Increasing reliability, security, and quality of railways are set as goals of European Commission. Hence, we will aim to find the best maintenance strategies for failure modes in a turnout system.

4.1 CASE STUDY 1

There are 25 failure modes with number of occurrences and downtime reported in (Marquez et al., 2008). We have categorized the failure modes are according to the component that the failure occurs. We have not considered failure modes No Fault

Found (NFF), Tested Ok (TOK), and Error/Negligence, which were reported in (Marquez et al., 2008), since they are actually not failure modes and difficult to detect using CBM. Categorized failure modes with downtime and occurrence information are given in Table 4.1.

Actions for maintenance and/or repair and their costs were calculated approximately with the help of experts in Turkish State Railways. Figure 4.1 illustrates a maintenance-repair action decision tree for turnout system. Nodes (actions) in action decision tree are accompanied with a probability value, which basically is the probability of performing that action as shown in Figure 3.4 before.

Table 4.1 Input data for case study 1

	No	*Failure Modes*	*freq*	*Downtime*	*Scale*	*Shape*
Drive Rod	1	Drive Rod Out of Adjustment (OOA)	8	2445	227	4
	2	Detector Rod Out of Adjustment	4	426	360	2
	3	Drive Rod Defective	7	12	250	2
	4	Detector Rod Defective	1	10	576	3
Slide Chair	5	Slide Chair Defective	1	773	458	6
	6	Slide Chair Obstructed/Contaminated	3	655	396	3
	7	Slide Chair Dry/Seized	15	441	110	3
Motor	8	Motor Brush Defective	2	85	400	7
	9	Commutator Defective	1	19	458	6
Detection Assembly	10	Contact Defective	3	144	396	3
	11	Detector Assembly HR	1	68	722	2
	12	Detection Assembly defective	5	46	315	2
	13	Detection Assembly OOA	2	45	400	7
Other	14	Micro switch Defective	1	714	576	3
	15	Relay Defective	4	154	360	2
	16	Stretch/Tie Bar Defective	19	84	86	2
	17	Face Point Lock	7	878	250	2
	18	Fuse Defective	7	235	250	2
	19	Stud Bolt Defective	6	26	281	2
	20	Cutout Reset Defective	2	12	407	6
	21	Heater Defective	1	0	510	4
	22	Cable Defective	1	0	477	5

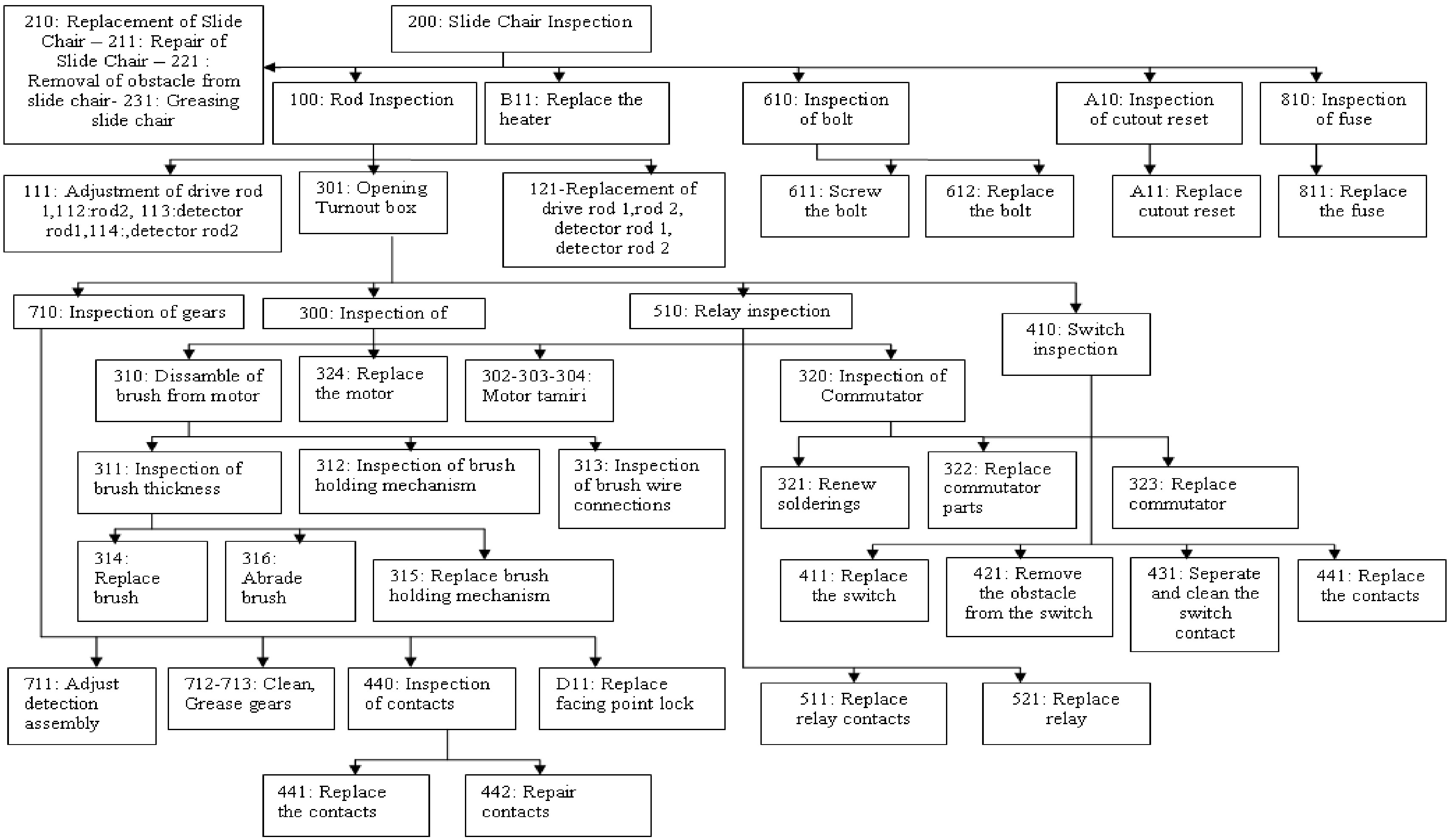


Figure 4.1 Action Decision Tree for Repair-Maintenance

Action decision tree and/or action probabilities may vary for repair, maintenance, or inspection as well as for maintenance strategies of CM, PM, and CBM. In CM, repair is performed after failure is occured, which involves inspection, identification of failure, waiting for required parts, and performing the repair. In PM, some pre-determined actions are performed, which will take less time with less variance than repair actions such as changing cables, lubricating machinery etc. In our applications, the time and cost of the maintenance are calculated by multiplying the repair time and cost by coefficient of 0.6. Finally, in CBM we have time and cost of inspection actions, which are set by multiplying time and cost of maintenance by 0.8, as well as repair actions for missed failures, which are set the same as repair cost and time in PM.

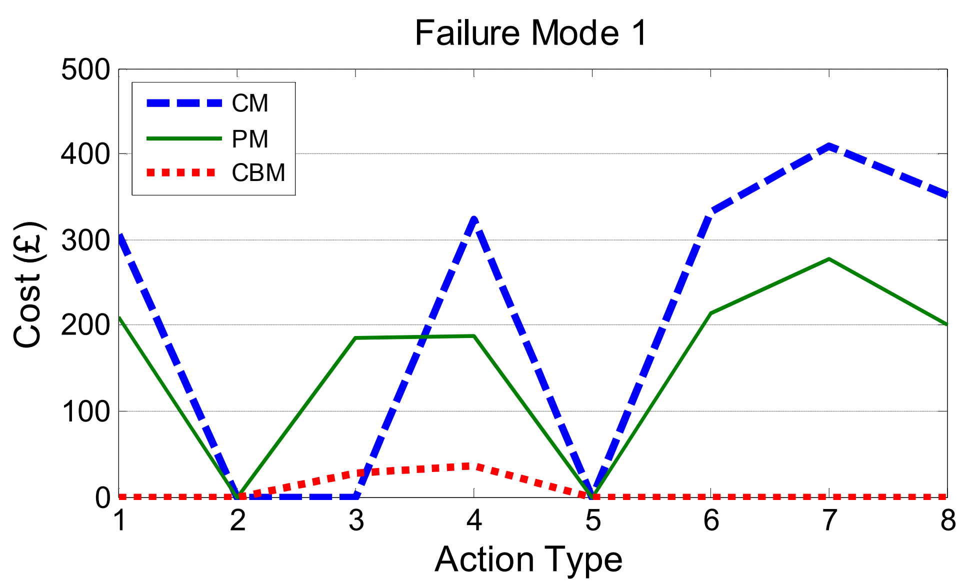


Figure 4.2 Costs of repair-maintenance actions for CM, PM, CBM

Figigure 4.2 displays the cost of repair-maintenance actions for maintenance strategies (CM, PM, CBM) for 8 actions. *x*-axis in the figure displays the actions, some of which are not performed in some strategies. For example, action number 3 is zero in CM since it is a specific action performed in PM and CBM. In contrary, action 4 is performed in CM, PM, and CBM with different costs (high in CM due to unexpected nature of the failure, little high in PM due to unnecessary details , and low in CBM with only required details).

Expected downtime is also one of the major components of the economic model. Reliability data is employed for calculation of expected number of failures. It is assumed that the reliability data follows Weibull distribution. Number of failures occurred in 3.5 years are given in (Marquez et al., 2008). It is possible to use this number as expected number of failures in 3.5 years, however, expected number of failures with different periodic maintenance periods could not be calculated without reliability data. Scale and shape parameters of reliability distribution are found by simulation and values that result close expected number of failures to the number of failures occurred in 3.5 years are selected...

Figure 4.3 shows expected downtime, which is used in calculation of delay cost due to maintenance or failure for all 22 failure modes under CM, PM, and CBM. As seen from the figure, expected downtime is highest in CM, low in PM, lowest in CBM.

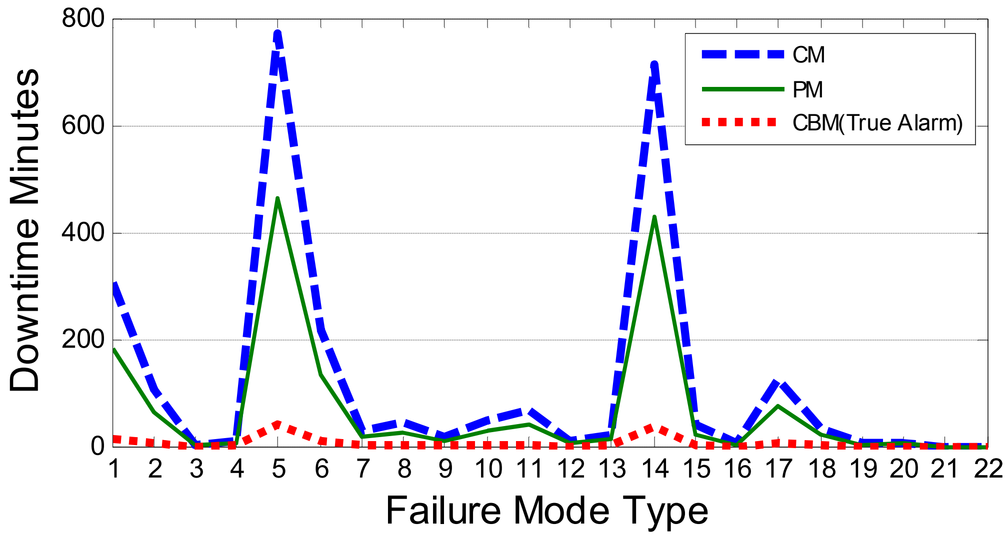


Figure 4.3 Expected Downtime for 22 failure modes

In addition to parameters used in CM, PM requires maintenance period as input parameter. Number of maintenance activities in given period is directly related with maintenance period and optimized using trial-error method. It initially is assumed one, and increased one by one until the increase in maintenance cost exceeds the reduction in failure cost. Thus, the best maintenance period is selected for PM. With the best maintenance period, expected number of failures is calculated as described before and demonstrated in Figure 3.5.

We have calculated cost for all maintenance policies and results are given in Table 4.2. Accuracy and probability prevention values given in (Marquez et al., 2008) are used in this calculation. As seen from the table, CM gives the minimum cost for failure modes 3, 4, 9, 11, 13, 15, 19, 20, and 22. PM is best for failure modes 8, 12, 18 and 21. CBM is the best policy for the rest of failure modes. These results of course highly depend on the accuracy of detection methods. The sensitivity analysis will be given in the next section.

Table 4.2 Cost of CM, PM, CBM for Case Study 1

	CM	PM	CBM	ψ_j
1	£40.324,10	£29.988,68	**£18.358,30**	0,6
2	£8.954,68	£10.919,89	**£6.124,55**	0,4
3	**£779,61**	£1.395,60	£1.098,61	0,4
4	**£664,59**	£1.690,64	£794,59	0
5	£12.676,74	£26.482,74	**£8.490,72**	0,4
6	£11.594,83	£12.033,35	**£5.634,82**	0,6
7	£16.300,42	£11.693,51	**£7.515,57**	0,6
8	£2.532,14	**£2.377,79**	£2.573,10	0,2
9	**£773,90**	£1.642,16	£847,73	0,6
10	£3.605,28	£3.790,61	**£2.110,71**	0,6
11	**£1.441,21**	£3.715,74	£1.675,17	0,2
12	£3.761,86	**£3.513,81**	£3.554,33	0,2
13	**£1.058,77**	£1.507,12	£1.374,59	0,2
14	£10.675,74	£28.406,60	**£7.228,44**	0,4
15	**£3.201,73**	£3.790,10	£3.475,17	0,08
16	£2.923,88	£3.634,25	**£2.512,75**	0,4
17	£15.545,27	£15.394,03	**£10.321,55**	0,4
18	£5.033,16	**£4.621,20**	£4.792,29	0,08
19	**£2.850,04**	£8.863,91	£2.976,04	0
20	**£527,18**	£980,00	£661,18	0
21	£694,74	**£665,47**	£824,74	0
22	**£584,48**	£1.096,32	£705,48	0

4.2 CASE STUDY 2

In this case study, data are obtained from experts in Turkish State Railways. Seven failure modes exist in this dataset with number of occurrences from 2000 to 2008 in one region of Turkish State Railways. Table 4.3 displays the failure modes, their frequency, downtime, and Weibull scale and shape parameters.

Table 4.4 displays the cost of maintenance policies for all failure modes. As seen from the figure, all failure modes should be maintained with CBM based on the parameters used.

Table 4.3 Input data for case study 2

	freq	*downtime*	*Downtime per a failure*	*Scale*	*Shape*
FM1	10,4	68644	730,3	42	2
FM2	10,1	32880	361,3	41	6
FM3	5,6	8549	171,0	78	6
FM4	2,7	6425	267,7	194	3
FM5	2,2	5521	276,1	238	4
FM6	0,2	275	137,5	476	6
FM7	0,1	120	120,0	755	3

Table 4.4 Cost of CM, PM, and CBM for case study 2

	CM	**PM**	**CBM**	ψ_j
1	429.366,51 TL	565.796,29 TL	**143.677,18 TL**	0.72
2	217.626,48 TL	191.562,65 TL	**73.842,15 TL**	0.72
3	53.814,70 TL	48.783,22 TL	**19.352,93 TL**	0.72
4	44.429,88 TL	34.007,34 TL	**15.702,58 TL**	0.72
5	37.085,45 TL	23.876,87 TL	**13.303,25 TL**	0.72
6	1.822,05 TL	5.755,49 TL	**1.635,54 TL**	0.72
7	**994,17 TL**	4.932,52 TL	1.292,71 TL	0.72

4.3 SENSITIVIY ANALYSIS

The presented economic analysis model involves several parameters that highly affect the results such as accuracy of diagnostics method (probability detection), expected downtime or expected number of failures. In this section, the sensitivity analysis of these parameters will be performed. The cost is reported in *y-axis,* whereas the parameter to be analyzed is given in *x-axis*. Note that CBM involves fixed investment and operating & support cost. Thus, in the first analysis, the total system cost is reported with the selected parameter. Two total system cost values for each parameter is calculated: one with CBM and one without CBM. In the former one, the best maintenance policy among PM and CM is selected for each failure mode and total cost is calculated based on these selections. In the latter, the best maintenance policy among CM, PM, and CBM is selected for each failure mode and total system cost is calculated. If CBM is selected for at least one failure mode, then the fixed cost of CBM is added to total system cost. Both costs for downtime are plotted in Figure 4.4. As seen from the figure, when the downtime is low, the benefit of CBM becomes less than the investment and operating & support cost. Applying combination of CM and PM for all failure modes is less costly compared to CBM due to initial investment and operating & support cost. When downtime exceeds 80, more than investment cost and operation cost of CBM is gained by applying CBM in the given time period. In other words, the downtime should at least be 80, in order to gain from the CBM investment in the given period. Note that analysis of downtime cost per minute will be similar, since downtime and cost per minute downtime are multiplied in the formulas.

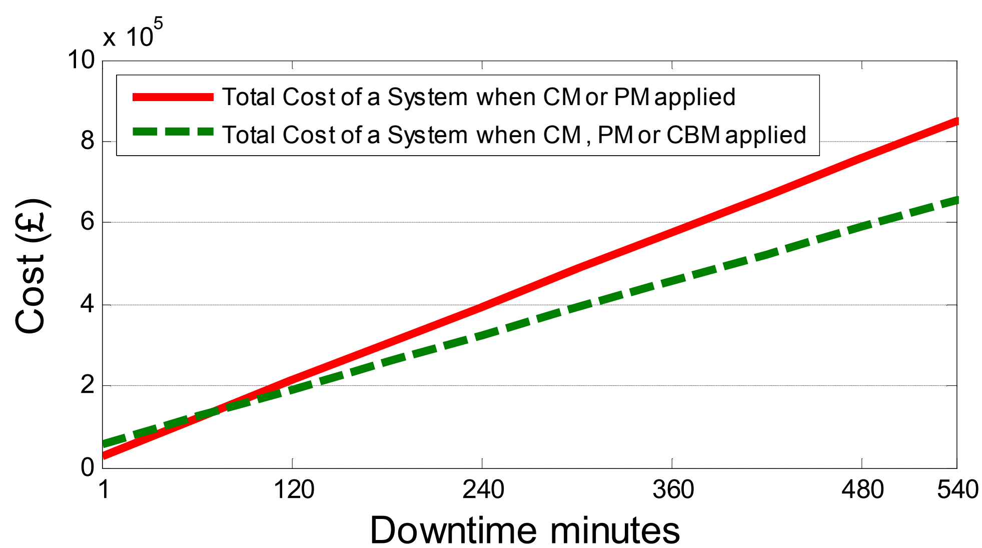


Figure 4.4 Total System Cost with and without CBM as downtime increases

Note that this analysis is done within given time period, which may be a year, 10 years, or life cycle. This analysis is true when the time period is long enough to cover the life cycle. If the time period is small like a year, then multiple periods should be analyzed since the investment cost is spent only in the first time period, not in the following time periods. Figure 4.5 illustrates this analysis by increasing the investment cost and calculating the turnover year for each investment cost. *x-axis* gives the investment cost, whereas *y-axis* gives the turnover year, which represents the number of years required to gain benefit equal to the initial investment cost from CBM.

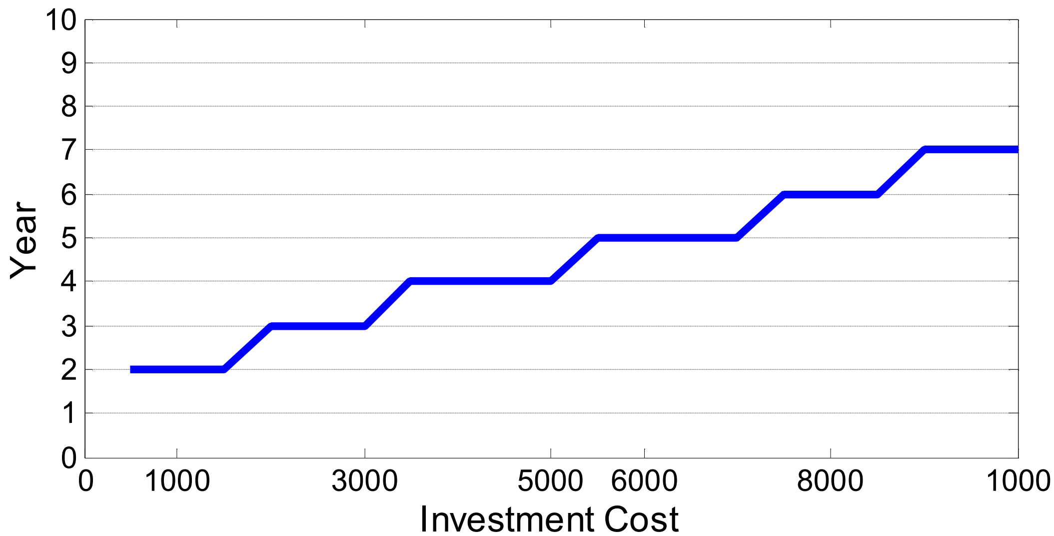


Figure 4.5 Turn over year vs. CBM investment cost

The analysis of the parameters for each failure mode might be more valuable. Thus, the remaining sensitivity analysis will be performed for a selected failure mode. Incorporation of CBM fixed cost on individual failure mode will be performed in two ways: totally added (CBM2) and distributed fixed (CBM1) cost. In the former, the fixed cost is added completely to the cost of failure mode 1 as if no other failure mode requires CBM. In other words, CBM is considered to be invested only for the selected failure mode. In the latter, CBM fixed cost is evenly distributed over all the failure modes. In all remaining sensitivity analysis, both costs will be displayed. Figure 4.6 displays the cost for CM, PM, and CBM for failure 1 as the downtime increases. Two CBM costs (i.e., fixed cost added and distributed) are displayed in the figure. As seen from the figure, when the downtime is close to 0, the costs for all policies are close to 0. The increase rate is highest in CM, high in PM, and lowest in CBM. When the downtime exceeds 1200, the benefit of applying CBM to only failure mode 1 is greater than the investment, operating and support cost of CBM. If CBM is applied to all failure modes and fixed cost is distributed to all failure modes, than the benefit of CBM is greater than the investment cost of CBM for failure mode 1.

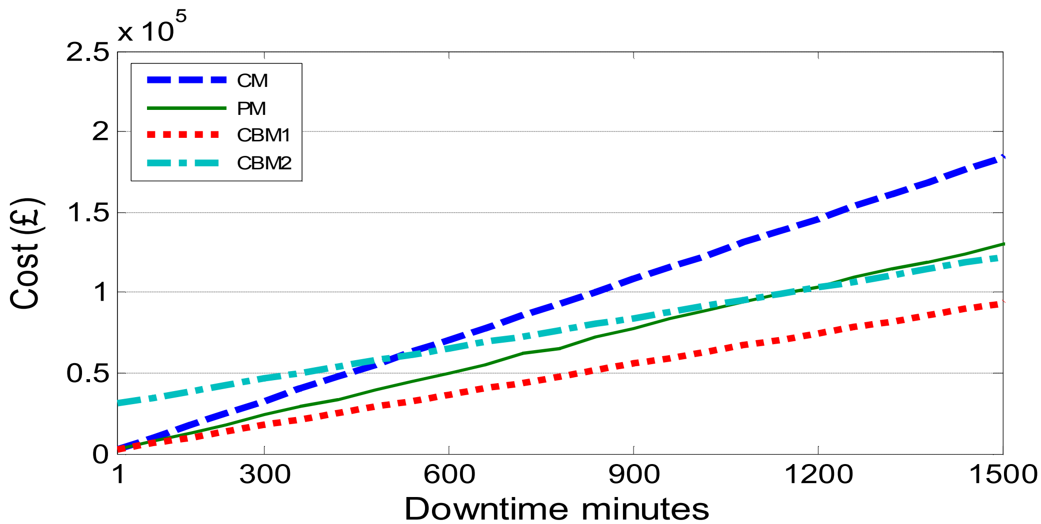


Figure 4.6 Cost of CM, PM, CBM for FM1 vs. Downtime

Second parameter to be analyzed is the product of detection rate of diagnostics method. Figure 4.7 displays the change of cost for maintenance policies with change in this parameter. As seen the figure, PM is minimum if the accuracy is less than 0.3. If it is greater than 0.3, CBM is minimum when the fixed cost of CBM is distributed to failures. It is understood that the investment cost will return in the given time period when CBM is applied to all failure modes and detection rate of all diagnostics method is greater than %30. Even if CBM is applied to only this failure mode, the cost of CBM approximates the cost of PM when detection rate is close to 1. This table helps to identify the minimum desired detection rate of a diagnostics method, whose investment and operating & support cost will return in the given time period as benefit.

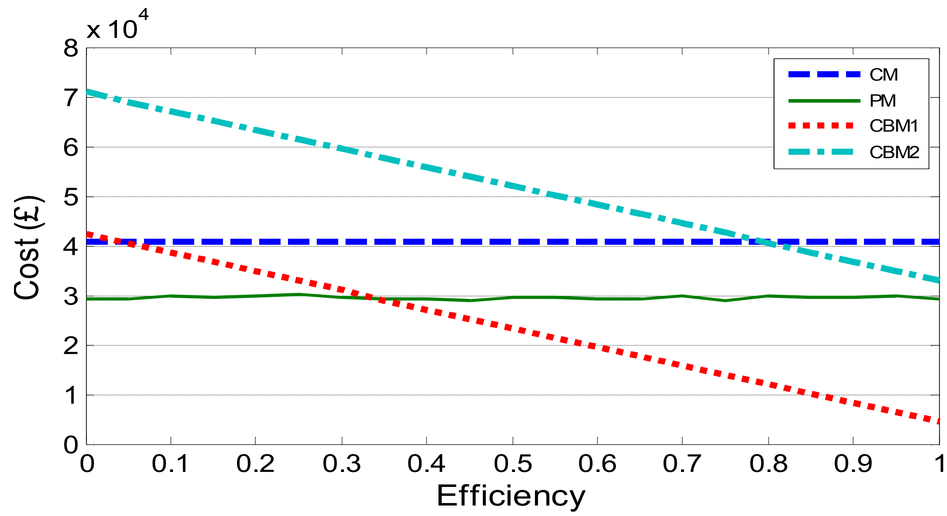


Figure 4.7 Cost of CM, PM, CBM for FM1 as detection rate increases

Figure 4.8 displays the changes in cost of maintenance policies with changes in cost of action. Cost of all maintenance policies increase with the increase in cost of actions. The increases have fluctuations due to the stochastic nature of expected number of failures calculation. As seen from the figure, the increase rate is smallest in CBM, since the actions are performed least in this policy. CBM1 is smallest for all action costs and CBM2 becomes smallest when action cost exceeds 5000. This means that CBM becomes beneficial in the given time period even CBM is applied to only one failure mode when the action cost is very high.

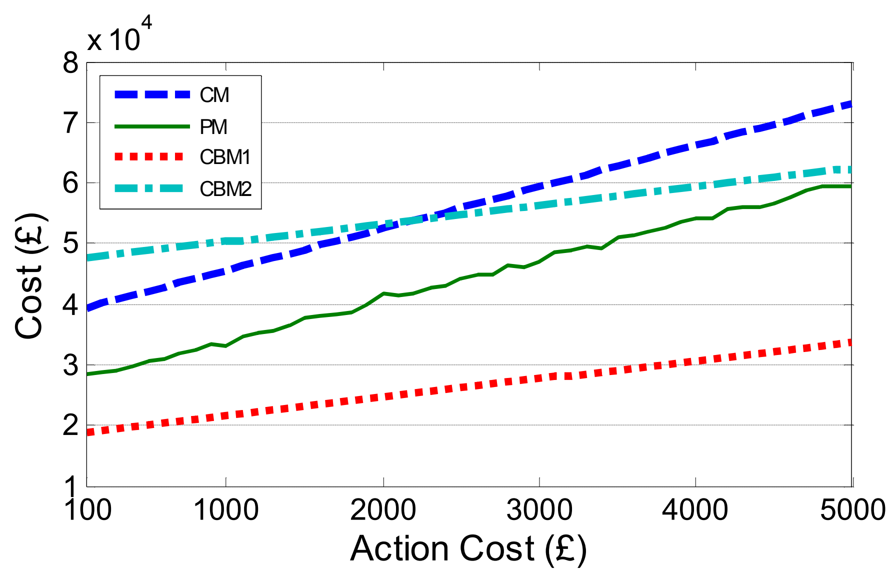


Figure 4.8 Cost of CM, PM, CBM for FM 1

Figure 4.9 illustrates the change in cost with number of periodic maintenance. When no periodic maintenance is performed, cost of PM becomes equal to CM. As the number of periodic maintenance is increased, the cost of PM decreases till some point. Then, it starts increasing as illustrated in Figure 4.9. The costs of CM and CBM do not change with the change in number of periodic maintenance. As seen from the figure, CBM with distributed cost is less than PM cost. When fixed investment cost is added to the CBM cost of failure 1, then the cost of CBM is seen high. However, this is true only first time period, which is displayed in the figure. When multiple periods are considered, this will change as demonstrated in Figure 4.5. Also note that when an investment for CBM done, multiple failure modes will be maintained with CBM.

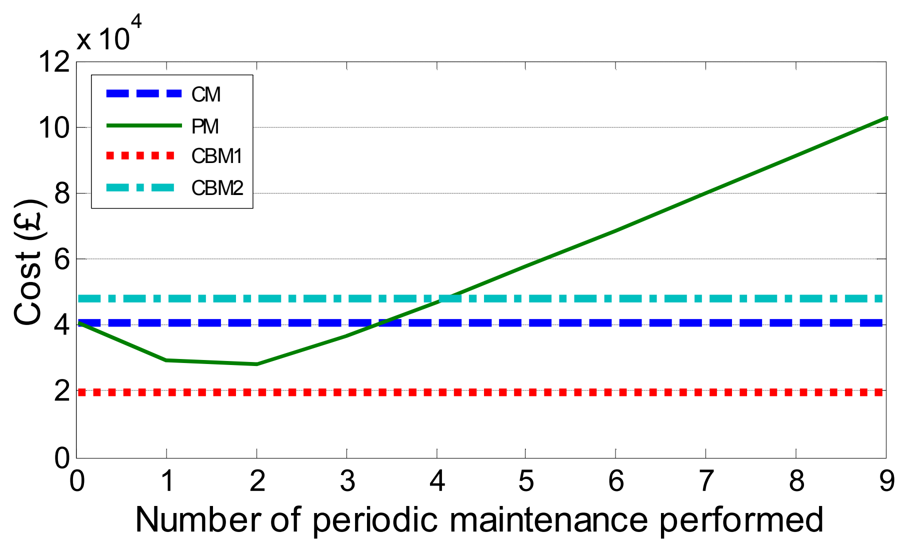


Figure 4.9 Cost of CM, PM, for FM1 as action number of PM increases

Figure 4.10 displays the costs of CM, PM and CBM with investment cost. As the investment cost increases, cost of CBM increases. One can understand the amount of investment to be done for CBM, which will return the investment as benefit within the given time period, using this figure.

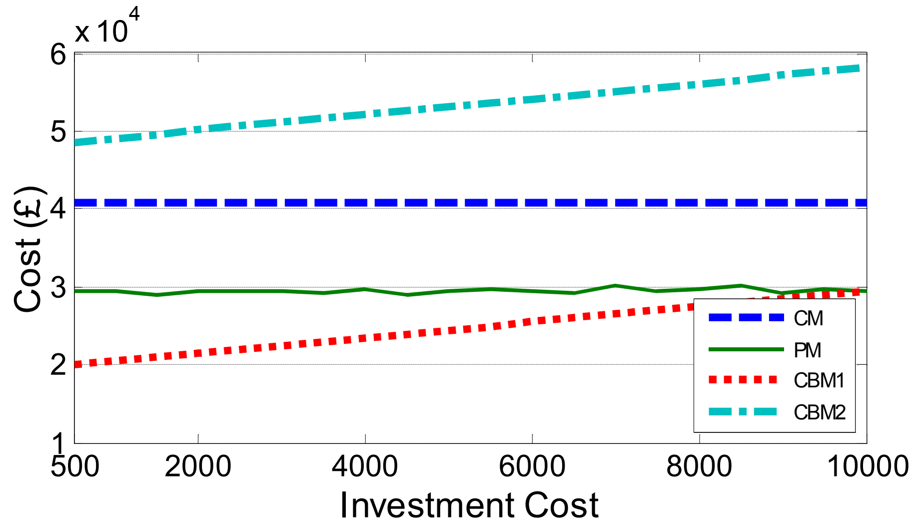


Figure 4.10 Cost of CM, PM, CBM for FM1 as Investment Cost increases

It is demonstrated in the case studies presented in the thesis that applying CBM for all failure modes may not be the best decision. In other words, preventive maintenance even corrective maintenance may be enough for some of the failures depending on its criticality. In case the first case study, failure modes whose repair cost is low like 19th, 20th and 22nd failure modes, it is proved that preventive maintenance is much more expensive than corrective, thus repairing them whenever failure occurs is best way to be implemented in maintenance planning. On the other hand, the analysis in the second case study shows that CBM is best for all failure modes. Result depends on the criticality of failure modes, their effects and cost required for applying CBM.

In addition, we have also concluded that maintenance planning system should be composed of all three maintenance strategies, namely Corrective, Periodic and Condition Based Maintenances. However number of failure modes, which should be maintained by Condition Based Maintenance is 16 in first case study or by other words 72% of all failure modes. This factor shows how CBM reduces the overall cost.

CHAPTER 5
CONCLUSIONS

CBM attracts researchers and industry in recent years with the ability to decrease system operating & support cost, increase availability and safety. Even though CBM leads to many benefits, initial investment cost cause hesitation about CBM. A detailed economic analysis of CBM that helps decision makers to analyze the benefits of CBM is needed. This paper presents an economic analysis method that aims to identify the best maintenance policy for each failure mode of a system. Repair and maintenance cost for corrective, preventive, and condition based maintenance policies are considered in cost calculation.

An economic analysis method is composed of three main sections which are Corrective, Periodic and Condition Based maintenances. In corrective maintenances there is only failure cost, because no preventive maintenance is performed and the system is repaired when it breakdown. However, Periodic maintenance cost includes two terms: repair and maintenance cost. Maintenance cost is the cost caused from periodic actions performed in order to prevent a failure to occur. Different from PM and CM, Condition Based Maintenance (CBM) requires investment, and operating costs. Investment cost is the cost of development, testing, installation of CBM technologies, training personnel, etc. for the system. Operating cost is the cost of making CBM up and running including replacement of sensors or other equipment when necessary.

Presented economic model is applied to two cases studies in turnout machines in railway systems. Data in first case study is taken from journal paper (Marquez et al., 2008) and we have twenty two failure modes. Second dataset, where there are seven failure modes, was supplied by Istanbul Railways. Our economic model suggested that CM gives the minimum cost for failure modes 3, 4, 9, 11, 13, 15, 19, 20, and 22. PM is best for failure modes 8, 12, 18 and 21. CBM is the best policy for the rest of failure modes. And for second case study for all failure modes except last should be applied condition based maintenance. Corrective Maintenance gives minimum cost for last failure mode.

Monte-Carlo simulation is used for estimation of expected number of failures to be occurred given number of maintenance actions. Sensitivity analysis of parameters investment cost, number of periodic maintenance, action cost, detection rate, and downtime was done.

It is demonstrated in the case studies presented in the thesis that applying CBM for all failure modes may not be the best decision. Best maintenance policy for the failure modes are identified based on the criticality of failure modes and cost required to apply CBM.

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